

# Greedy Attack and Gumbel Attack: Generating Adversarial Examples for Discrete Data

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## Abstract

We present a probabilistic framework for studying adversarial attacks on discrete data. Based on this framework, we derive a perturbation-based method, *Greedy Attack*, and a scalable learning-based method, *Gumbel Attack*, that illustrate various tradeoffs in the design of attacks. We demonstrate the effectiveness of these methods using both quantitative metrics and human evaluation on various state-of-the-art models for text classification, including a word-based CNN, a character-based CNN and an LSTM. As an example of our results, we show that the accuracy of character-based convolutional networks drops to the level of random selection by modifying only five characters through Greedy Attack.

**Keywords:** Adversarial Attack

## 1. Introduction

Robustness to adversarial perturbation has become an extremely important criterion for applications of machine learning in many security-sensitive domains such as spam detection (Stringhini et al., 2010), fraud detection (Ghosh and Reilly, 1994), criminal justice (Berk and Bleich, 2013), malware

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detection (Kolter and Maloof, 2006), and financial markets (West, 2000). Although it is not surprising that some small perturbations can change the prediction of an ML model, it is nontrivial to find those perturbations. For instance, random sampling usually cannot find those adversarial examples. Therefore, systematic methods for generating adversarial examples by small perturbations of original input data, also known as “attack,” have been developed to operationalize this criterion and to drive the development of more robust learning systems (Dalvi et al., 2004; Szegedy et al., 2013; Goodfellow et al., 2014).

Most of the work in this area has focused on differentiable models with continuous input spaces (Szegedy et al., 2013; Goodfellow et al., 2014; Kurakin et al., 2016). In this setting, the proposed attack strategies add a gradient-based perturbation to the original input, resulting in a dramatic decrease in the predictive accuracy of the model. This finding demonstrates the vulnerability of deep neural networks to adversarial examples in tasks like image classification and speech recognition.

We focus instead on adversarial attacks on models with discrete input data, such as text data, where each feature of an input sample has a categorical domain. While gradient-based approaches are not directly applicable to this setting, variations of gradient-based approaches have been shown effective in differentiable models. For example, Li et al. (2015) proposed to locate the top features with the largest gradient magnitude of their embedding, and Papernot et al. (2016) proposed to modify randomly selected features of an input through perturbing each feature by signs of the gradient, and project them onto the closest vector in the embedding space. Dalvi et al. (2004) attacked such models by solving a mixed integer linear program. Gao et al. (2018) developed scoring functions applicable for sequence data, and proposed to modify characters of the features selected by the scoring functions. Attack methods specifically designed for text data have also been studied recently. Jia and Liang (2017) proposed to insert distraction sentences into samples in a human-involved loop to fool a reading comprehension system. Samanta and Mehta (2017) added linguistic constraints over the pool of candidate-replacing words. Cheng et al. (2018) applied a gradient-based technique to attack sequence-to-sequence models.

We propose a systematic probabilistic framework for generating adversarial examples for models with discrete input. The framework is a two-stage process, where the key features to be perturbed are identified in the first stage and are then perturbed in the second stage by values chosen from a dictionary. We present two instantiations of this framework—*Greedy Attack* and *Gumbel Attack*. Greedy Attack evaluates models with single-feature perturbed inputs in two stages, while Gumbel Attack learns a parametric sampling distribution for perturbation. Greedy Attack achieves higher success rate, while Gumbel Attack requires fewer model evaluations, leading to better efficiency in real-time or large-scale attacks. Table 1 compares our methods with other methods qualitatively. A method is labeled as efficient if the average clock time for perturbing a single example is beyond one second for any of the three data sets in Figure 4. See Section 4 for a detailed quantitative comparison.

In summary, our contributions in this work are as follows:

- We propose a probabilistic framework for adversarial attacks on models with discrete data.
- We show that Greedy Attack achieves state-of-the-art attack success rates across various kinds of models.
- We propose Gumbel Attack as a scalable method with low model-evaluation complexity.
- We observe that character-based models in text classification are particularly vulnerable to adversarial attack.

Attack Methods	Training	Efficiency	Success rate	Black-box
Saliency (Simonyan et al., 2013)	No	High	Medium	No
Projected FGSM (Papernot et al., 2016)	No	High	Low	No
Delete 1-score (Li et al., 2016)	No	Low	High	Yes
DeepWordBug (Gao et al., 2018)	No	Low	Medium	Yes
Greedy Attack	No	Low	Highest	Yes
Gumbel Attack	Yes	High	Medium	Yes

Table 1: Methods comparisons. “Efficiency”: computational time and model evaluation times. “Black-box”: applicability to black-box models. See Section 4 for details.

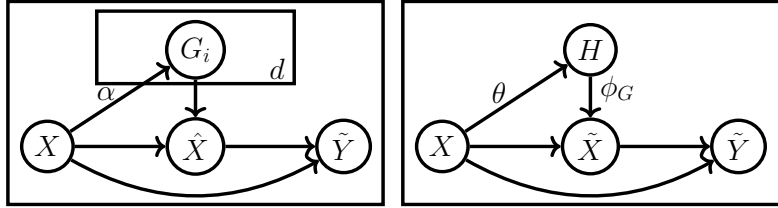


Figure 1: The left and right figures show the graphical models of the first and second stage respectively. Parameters  $\alpha$ ,  $\theta$  and  $\phi_G$  are specific to Gumbel Attack (Algorithm 2).

## 2. Framework

We assume a model in the form of a conditional distribution,  $\mathbb{P}_m(Y | x)$ , for a response  $Y$ , supported on a set  $\mathcal{Y}$ , given a realization of an input random variable  $X = x \in \mathbb{W}^d$ , where  $\mathbb{W} := \{w_0, w_1, \dots, w_m\}$  is a discrete space such as the dictionary of words or the space of characters. We assume there exists  $w_0 \in \mathbb{W}$  that can be taken as a reference point with no contribution to classification. For example,  $w_0$  can be the zero padding in text classification. Let  $\tilde{x}$  denote a perturbation of the input variable  $x$ . The goal of the adversarial attack is to turn a given input  $x$  into  $\tilde{x}$  through small perturbations, in such a way that  $\tilde{Y} = 1$  given  $\tilde{x}$ , where  $\tilde{Y}$  is the indicator of a successful attack:  $\tilde{Y} | \tilde{x}, x := \mathbf{1}\{\arg \max_y \mathbb{P}_m(y | \tilde{x}) \neq \arg \max_y \mathbb{P}_m(y | x)\}$ . We restrict the perturbations to  $k$  features of  $x$ , and approach the problem through two stages. In the first stage, we search for the most important  $k$  features of  $x$ . In the second stage, we search for values to replace the selected  $k$  features:

$$\text{First stage: } \hat{x} = \arg \max_{a \in S_1(x, k)} \mathbb{P}(\tilde{Y} = 1 | a, x), \quad (1)$$

$$\text{Second stage: } \tilde{x} = \arg \max_{a \in S_2(\hat{x}, x)} \mathbb{P}(\tilde{Y} = 1 | a, x), \quad (2)$$

where  $S_1(x, k) := \{a \in \mathbb{W}^d \mid a_i \in \{x_i, w_0\} \text{ for all } i, D(a, x) \leq k\}$  is a set containing all the elements that differ from  $x$  by at most  $k$  positions, with the different features always taking value  $w_0$ , and  $S_2(\hat{x}, x) := \{a \in \mathbb{W}^d \mid a_i = \hat{x}_i \text{ if } \hat{x}_i = x_i; a_i \in \mathbb{W}' \text{ otherwise}\}$ . Here, we denote by  $x_i, a_i, \hat{x}_i$  the  $i$ th feature of  $x, a, \hat{x}$ , by  $D(a, x)$  the count of features different between  $a$  and  $x$ , and by  $\mathbb{W}' \subseteq \mathbb{W}$  a sub-dictionary of  $\mathbb{W}$  chosen by the attacker.

These two objectives are computationally intractable in general. We thus further propose a probabilistic framework to reformulate the objectives into a more tractable objective, as shown in Figure 1. Let  $G$  be a random variable in  $D_k^d := \{z \in \{0, 1\}^d : \sum z_i \leq k\}$ , the space of  $d$ -dimensional zero-one vectors with at most  $k$  ones, and let  $\phi : \mathbb{W}^d \times D_k^d \rightarrow \mathbb{W}^d$  be a function such that  $\phi(x, g)_i = x_i$  if  $g_i = 0$  and  $\phi(x, g)_i = w_0$  if  $g_i = 1$ . In the first stage, we let  $\hat{X} = \phi(X, G)$  where  $G$  is generated from a distribution conditioned on  $X$ . We further add a constraint on  $\mathbb{P}(G|X)$ , by defining  $k$  independent and identically distributed one-hot random variables  $G^1, G^2, \dots, G^k \in D_1^d$  conditioned on  $X$ , and letting  $G_i := \max_s \{G_s^i\}$ , with  $G_i$  and  $G_i^l$  being the  $i$ th entries of the variables  $G$  and  $G^l$  respectively. We aim to maximize the objective  $\mathbb{P}(\tilde{Y} = 1 | \hat{X}, X)$  over the distribution of  $G$  given  $X$ , the probability of successful attack obtained by merely masking features:

$$\max_{\mathbb{P}(G|x)} \mathbb{E}_X[\mathbb{P}(\tilde{Y} = 1 | \hat{X}, X)], \text{ s.t. } \hat{X} = \phi(X, G), G^l \stackrel{i.i.d.}{\sim} \mathbb{P}(\cdot | X), \tilde{Y} \sim \mathbb{P}(\tilde{Y} | \hat{X}, X). \quad (3)$$

The categorical distribution  $\mathbb{P}(G^l | x)$  yields a rank over the  $d$  features for a given  $x$ . Let  $\mathcal{P}_k([d])$  be the set of subsets of  $[d]$  of size  $k$ . We define  $\phi^G : \mathbb{W}^d \rightarrow \mathcal{P}_k([d])$  to be the deterministic function that maps an input  $x$  to the indices of the top  $k$  features based on the rank from  $\mathbb{P}(G^l | x)$ :  $\phi^G(x) = \{i_1, \dots, i_k\}$ .

In the second stage, we introduce a new random variable  $H = (H^1, \dots, H^d)$  with each  $H^i$  being a one-hot random variable in  $D_1^{|\mathbb{W}'|} := \{z \in \{0, 1\}^{|\mathbb{W}'|} : \sum z_i = 1\}$ . Let  $\psi : \mathbb{W}^d \times (D_1^{|\mathbb{W}'|})^d \times \mathcal{P}_k([d]) \rightarrow \mathbb{W}^d$  be a function such that  $\psi(x, h, \phi^G(x))_i$  is defined to be  $x_i$  if  $i \notin \phi^G(x)$ , and is the value in  $\mathbb{W}'$  corresponding to the one-hot vector  $h_i$  otherwise. The perturbed input is  $\tilde{X} := \psi(X, H, \phi^G(X))$ , where  $H$  is generated from a distribution conditioned on  $X$ . Our goal is to maximize the objective  $\mathbb{P}(\tilde{Y} = 1 | \tilde{X}, X)$  over the distribution of  $H$  given  $X$ :

$$\max_{\mathbb{P}(H|x)} \mathbb{E}_{X,G}[\mathbb{P}(\tilde{Y} = 1 | \tilde{X}, X)], \text{ s.t. } \tilde{X} = \psi(X, H, \phi^G(X)), H \sim \mathbb{P}(\cdot | X), \tilde{Y} \sim \mathbb{P}(\tilde{Y} | \tilde{X}, X). \quad (4)$$

For a given input  $x$ , the categorical distribution  $\mathbb{P}(H^i | x)$  yields a rank over the values in  $\mathbb{W}'$  to be chosen for each feature  $i$ . The perturbation on  $x$  is carried out on the top  $k$  features  $\phi^G(x) = \{i_1, \dots, i_k\}$  ranked by  $\mathbb{P}(G^l | x)$ ; each chosen feature  $i_s$  is assigned the top value in  $\mathbb{W}'$  selected by  $\mathbb{P}(H^{i_s} | x)$ .

### 3. Methods

In this section we present two instantiations of our general framework: *Greedy Attack* and *Gumbel Attack*.

#### 3.1. Greedy Attack

We motivate Algorithm 1, Greedy attack, as optimizing the lower bounds of Problem (3) and Problem (4). To solve Problem (3), we decompose the objective conditioned on a single instance  $x$  as:

$$\mathbb{E}_{G|X}[\mathbb{P}(\tilde{Y} = 1 | \hat{X}, X) | x] = \sum_{i=1}^d \mathbb{P}(G^1 = e_i | x) \mathbb{E}_{G^{(1)}|X, G^1}[\mathbb{P}(\tilde{Y} = 1 | \hat{X}, X) | x, e_i],$$

where  $e_i$  denote the  $d$ -dimensional one-hot vector whose  $i$ th component is 1, and  $G^{(1)} := (G^2, \dots, G^k)$ . We claim the objective in Problem 3 conditioned on a single instance  $x$  can be lower bounded as

$$\begin{aligned} & \max_{\mathbb{P}(G|x)} \mathbb{E}_{G|X} [\mathbb{P}(\tilde{Y} = 1 \mid \hat{X}, X) \mid x] \\ & \geq \max_{\mathbb{P}(G^1|x)} \sum_{i=1}^d \left( \mathbb{P}(G^1 = e_i \mid x) \max_{\mathbb{P}(G^{(1)}|x, e_i)} \mathbb{E}[\mathbb{P}(\tilde{Y} = 1 \mid \hat{X}, X) \mid x, e_i] \right) \\ & \geq \max_{\mathbb{P}(G^1|x)} \sum_{i=1}^d \mathbb{P}(G^1 = e_i \mid x) \mathbb{P}(\tilde{Y} = 1 \mid x_{(i)}), \end{aligned} \quad (5)$$

where  $x_{(i)}$  denotes the input constructed from  $x$  by replacing the  $i$ th feature of  $x$  with  $w_0$ . In fact, let  $\vee$  denote the elementwise maximum of a set of random vectors. We have

$$\begin{aligned} \max_{\mathbb{P}(G^{(1)}|x, e_i)} \mathbb{E}[\mathbb{P}(\tilde{Y} = 1 \mid \hat{X}, X) \mid x, e_i] &= \max_{\mathbb{P}(G^{(1)}|x, e_i)} \mathbb{E}[\mathbb{P}(\tilde{Y} = 1 \mid \phi(X, \vee\{e_i, G^{(1)}\}), X) \mid x, e_i] \\ &\geq \mathbb{P}(\tilde{Y} = 1 \mid \phi(x, \vee\{e_i, G^2 = e_i, \dots, G^k = e_i\})) \\ &= \mathbb{P}(\tilde{Y} = 1 \mid x_{(i)}). \end{aligned}$$

where the first equality follows from the definition of  $\hat{X}$ , and the inequality follows from degenerating  $\mathbb{P}(G^{(1)}|x, e_i)$ . The lower bound (5) is maximized when

$$\mathbb{P}(G^1 = e_i \mid x) \propto \mathbb{P}(\tilde{Y} = 1 \mid x_{(i)}). \quad (6)$$

Similarly, we decompose the objective in Problem (4) by conditioning on  $H^{i_1}$  and invoking the independence between  $G$  and  $H$  conditioning on  $X$ . Using a similar argument, we arrive at

$$\begin{aligned} & \max_{\mathbb{P}(H|x, g)} \mathbb{E}_{H|X, G} [\mathbb{P}(\tilde{Y} = 1 \mid \tilde{X}, X) \mid x, g] \\ &= \max_{\mathbb{P}(H^{i_1}|x, g)} \sum_{j=1}^{|\mathbb{W}|} \mathbb{P}(H^{i_1} = e_j \mid x, g) \max_{\mathbb{P}(H^{(i_1)}|x, e_j)} \mathbb{E}_{H^{(i_1)}|X, G, H^{i_1}} [\mathbb{P}(\tilde{Y} = 1 \mid \tilde{X}, X) \mid x, e_j] \\ &\geq \max_{\mathbb{P}(H^{i_1}|x, g)} \sum_{j=1}^{|\mathbb{W}|} \mathbb{P}(H^{i_1} = e_j \mid x, g) \mathbb{P}(\tilde{Y} = 1 \mid x_{(i_1 \rightarrow w_j)}). \end{aligned} \quad (7)$$

The lower bound (7) is maximized when

$$\mathbb{P}(H^{i_1} = e_j \mid x, g) \propto \mathbb{P}(\tilde{Y} = 1 \mid x_{(i_1 \rightarrow w_j)}). \quad (8)$$

The same applies to  $i_2, \dots, i_k$ . The algorithm Greedy Attack is built up from Equation (6) and Equation (8) in a straightforward manner. See Algorithm 1 for details.

While Greedy Attack is proposed in its most generic form, it is flexible to incorporate linguistic coherence for natural language tasks. GloVe (Pennington et al., 2014) is a widely used unsupervised learning algorithm to obtain vector representation of words. The Euclidean distance between two vector embeddings provides an effective method for measuring the semantic similarity of the corresponding words. Throughout experiments, we restrict the candidate pool in the second stage of Greedy Attack to words close to the original word in terms of the Euclidean distance of the corresponding vector embeddings, so as to keep the semantic meaning of the entire sentence.

### 3.2. Gumbel Attack

Algorithm 1 evaluates the original model  $\mathcal{O}(d + k \cdot |\mathbb{W}'|)$  times for each sample. In the setting where one would like to carry out the attack over a massive data set  $\mathcal{D}'$ , Greedy Attack can be infeasible due to the high cost of model evaluations. Assuming that the original model is differentiable and each sample in  $\mathcal{D}'$  is generated from a common underlying distribution, an alternative approach to solve Problem (3) and Problem (4) is to parametrize  $\mathbb{P}(G | x)$  and  $\mathbb{P}(H | x)$  and optimize the objectives over the parametric family directly on a training data set from the same distribution before the adversarial attack. An outline of this approach is described in Algorithm 2. We describe the training process in detail below.

Algorithm 1 Greedy Attack	Algorithm 2 Gumbel Attack
<p><b>Input:</b> Model <math>\mathbb{P}_m(Y   x)</math>.                      Sample <math>x \in \mathbb{W}^d</math>.  <math>k</math>, number of features to change.  <math>\mathbb{W}'</math>, sub-dictionary.</p> <p><b>Output:</b> Modified <math>x</math>.</p> <p><b>for</b> <math>i = 1</math> <b>to</b> <math>d</math> <b>do</b>                      Compute <math>\mathbb{P}(\tilde{Y}   x_{(i)})</math>.</p> <p><b>end for</b>  <math>i_1, \dots, i_k = \text{Top}_k(\mathbb{P}(\tilde{Y}   x_{(i)})_{i=1}^d)</math>.</p> <p><b>for</b> <math>s = 1</math> <b>to</b> <math>k</math> <b>do</b>  <math>x_{i_s} \leftarrow \arg \max_{w \in \mathbb{W}'} \mathbb{P}(\tilde{Y}   x_{(i_s \rightarrow w)})</math>.</p> <p><b>end for</b></p>	<p><b>Input:</b> Model <math>\mathbb{P}_m(Y   x)</math>.  <math>k</math>, number of features to change.                      A data set <math>\mathcal{D} = \{x_i\}</math> (for training).                      A data set <math>\mathcal{D}'</math> to be attacked.  <math>\mathbb{W}'</math>, sub-dictionary.</p> <p><b>Output:</b> Modified data set <math>\tilde{\mathcal{D}}'</math>.</p> <p>Train <math>\mathbb{P}_\alpha(G X)</math> on <math>\mathcal{D}</math>.                      Train <math>\mathbb{P}_\theta(H X)</math> on <math>\mathcal{D}</math> given <math>\mathbb{P}_\alpha(G X)</math>.</p> <p><b>for</b> <math>x</math> <b>in</b> <math>\mathcal{D}'</math> <b>do</b>  <math>i_1, \dots, i_k = \text{Top}_k(\mathbb{P}_\alpha(G x))</math></p> <p><b>for</b> <math>s = 1</math> <b>to</b> <math>k</math> <b>do</b>  <math>x_{i_s} \leftarrow \arg \max_{w \in \mathbb{W}'} \mathbb{P}_\theta(H^{i_s}   g, x)</math></p> <p><b>end for</b>                      Add the modified <math>x</math> to <math>\tilde{\mathcal{D}}'</math>.</p> <p><b>end for</b></p>

In the presence of  $k$  categorical random variables in Equation (3) and Equation (4), direct model evaluation requires summing over  $d^k$  terms and  $|\mathbb{W}'|^k$  terms respectively. A straightforward approximation scheme is to exploit Equations (5) and (7), where we assume the distribution of hidden nodes  $G$  and  $H$  is well approximated by greedy methods. Nonetheless, this still requires  $d + |\mathbb{W}'|^k$  model evaluations for each training sample. Several approximation techniques exist to further reduce the computational burden; e.g., one can take a weighted sum of features parametrized by deterministic functions of  $X$ , similar to the soft-attention mechanism (Ba et al., 2014; Bahdanau et al., 2014; Xu et al., 2015), and REINFORCE-type algorithms (Williams, 1992). We instead propose a method based on the ‘‘Gumbel trick’’ (Maddison et al., 2016; Jang et al., 2017), combined with the approximation of the objective proposed in Greedy Attack on a small subset of the training data. This achieves better performance with lower variance and higher model evaluation efficiency in our experiments.

The Gumbel trick involves using a Concrete random variable, introduced as a differentiable approximation of a categorical random variable, which has categorical probability  $p_1, p_2, \dots, p_d$  and is encoded as a one-hot vector in  $\mathbb{R}^d$ . The Concrete random variable  $C$ , denoted by  $C \sim \text{Concrete}(p_1, p_2, \dots, p_d)$ , is a random vector supported on the relaxed simplex  $\Delta_d := \{z \in [0, 1]^d :$

$\sum_i z_i = 1\}$ , such that  $C_i \propto \exp\{(\log p_i + \varepsilon_i)/\tau\}$ , where  $\tau > 0$  is the tunable temperature, and  $\varepsilon_j := -\log(-\log u_j)$ , with  $u_i$  generated from a standard uniform distribution, defines a Gumbel random variable.

In the first stage, we parametrize  $\mathbb{P}(G^l | x)$  by its categorical probability  $p_\alpha(x)$ , where

$$p_\alpha(x) = ((p_\alpha(x))_1, (p_\alpha(x))_2, \dots, (p_\alpha(x))_d),$$

and approximate  $G$  by a random variable  $U$  defined from a collection of Concrete random variables:

$$U = (U_1, \dots, U_d), U_i = \max_{s=1, \dots, k} \{C_i^s\},$$

where  $C_i^s \stackrel{i.i.d.}{\sim}$  Concrete  $(p_\alpha(x))$  for  $s = 1, \dots, k$ . We write  $U = U(\alpha, x, \varepsilon)$  as it is a function of the parameters  $\alpha$ , input  $x$  and auxiliary random variables  $\varepsilon$ . The perturbed input  $\hat{X} = \phi(X, G)$  is approximated by

$$\hat{X} \approx U \odot X, \text{ with } (U \odot X)_i := (1 - U_i) \cdot X_i + U_i \cdot w_0,$$

where we identify  $X_i, w_0$  and  $w_j$  with their corresponding embeddings for notation convenience.

In the second stage, we further add a constraint on  $\mathbb{P}(H | X)$  by requiring  $H^1, \dots, H^d$  to be independent of each other conditioned on  $X$ . We then parametrize  $\mathbb{P}(H | x)$  by another family  $q_\theta(x) = \{(q_\theta)_{ij}, i = 1, \dots, d; j = 1, \dots, |\mathbb{W}'|\}$ , and approximate each  $H^i$  by a Concrete random variable

$$V^i \sim \text{Concrete}((q_\theta)_{i1}, \dots, (q_\theta)_{i|\mathbb{W}'|}).$$

The perturbed input  $\tilde{X} = \psi(X, H, \phi^G(x))$  is approximated by replacing the  $i_s$  feature with a weighted sum of the embeddings of  $w \in \mathbb{W}'$  with entries of  $V^{i_s}$  as weights, for each  $i_s$  in  $\phi^G(x)$ :

$$\psi(X, H, \phi^G(X)) \approx V \odot_{\phi^G} X,$$

where

$$(V \odot_{\phi^G} X)_i := \begin{cases} \sum_{w_j \in \mathbb{W}'} V_j^i \cdot w_j & \text{if } i \in \phi^G(X), \\ X_i & \text{otherwise.} \end{cases}$$

The final objectives of Gumbel attack on a data set  $\mathcal{D}$  become the following:

$$\begin{aligned} \max_{\alpha} \quad & \frac{1}{|\mathcal{D}|} \sum_{x \in \mathcal{D}} \log f(U(\alpha, x, \varepsilon) \odot x), \\ \max_{\theta} \quad & \frac{1}{|\mathcal{D}|} \sum_{x \in \mathcal{D}} \log f(V(\theta, x, \varepsilon) \odot_{\phi^G} x), \end{aligned}$$

where we define  $f(x) := \mathbb{P}(\tilde{Y} = 1 | x)$  for notational convenience. Note that  $\varepsilon$  is an auxiliary random variable independent of the parameters. In the training stage, we can apply stochastic gradient methods directly to optimize the two objectives, where a mini-batch of unlabelled data and auxiliary random variables are jointly sampled to compute a Monte Carlo estimate of the gradient. In the attack stage, one directly perturbs incoming samples from a massive data set  $\mathcal{D}'$  based on the trained samplers  $\mathbb{P}_\alpha(G|X)$  and  $\mathbb{P}_\theta(H|X)$ , with no cost on model evaluation. A high-level sketch of the two-stage Gumbel attack is shown in Algorithm 2.

Data Set	Classes	Train Samples	Test Samples	Average #w	Model	Parameters	Accuracy
IMDB Review (Maas et al., 2011)	2	25,000	25,000	325.6	WordCNN	351,002	90.1%
AG’s News (Zhang et al., 2015)	4	120,000	7,600	278.6	CharCNN	11,337,988	90.09%
Yahoo! Answers (Zhang et al., 2015)	10	1,400,000	60,000	108.4	LSTM	7,146,166	70.84%

Table 2: Summary of data sets and models. “Average #w” is the average number of words per sample. “Accuracy” is the model accuracy on test samples.

## 4. Experiments

We evaluate the performance of our algorithms in attacking three text classification models, including a convolutional neural network (CNN) and a Long Short-Term Memory (LSTM) network. See Table 2 for a summary of the data and models used, and supplementary material for model details. During the adversarial attack, inputs are perturbed at their respective feature levels, and words and characters are units for perturbation for word and character-based models respectively. We compare Greedy Attack and Gumbel Attack with the following methods:

- **Delete-1 Score** (Li et al., 2016): Mask each feature with zero padding, use the decrease in the predicted probability as the score of the feature, and mask the top- $k$  features as unknown.
- **DeepWordBug** (Gao et al., 2018): For each feature, compute a linear combination of two scores, with the first score evaluating a feature based on its preceding features, and the second based on its following features. Weights are selected by the user.
- **Projected FGSM** (Goodfellow et al., 2014; Papernot et al., 2016): Perturb a randomly selected subset of  $k$  features by replacing the original word  $w$  with a  $w'$  in the dictionary such that  $\|\text{sgn}(\text{emb}(w') - \text{emb}(w)) - \text{sgn}(\nabla f)\|$  is minimized, where  $\text{emb}(w)$  is the embedding of  $w$ , and  $\nabla f$  is the gradient of the predicted probability with respect to the original embedding.
- **Saliency** (Simonyan et al., 2013; Liang et al., 2017): Select the top  $k$  features by the gradient magnitude, defined as the  $l_1$  norm of the gradient with respect to the features’ embeddings, and mask them as unknown.
- **Saliency-FGSM**: Select the top  $k$  features based on the Saliency map, and replace each of them using projected FGSM.

### 4.1. Word-based models

We use two word-based models: a word-based CNN network (Kim, 2014) and a word-based LSTM network (Hochreiter and Schmidhuber, 1997):

- **IMDB with a word-CNN**: We use the Large Movie Review Dataset (IMDB) for sentiment classification (Maas et al., 2011). It contains 50,000 binary labeled movie reviews, with a split of 25,000 for training and 25,000 for testing. The word-based CNN model consists of a 50-dimensional word embedding, a 1-D convolutional layer of 250 filters and kernel size 3, a max-pooling and a 250-dimensional dense layer as hidden layers. Both the convolutional and the dense layers are followed by ReLU as nonlinearity, and Dropout (Srivastava et al., 2014) as regularization. The model is trained with rmsprop (Hinton et al., 2012) for five epochs. Each review is padded/cut to 400 words. The model achieves accuracy of 90.1% on the test data set.



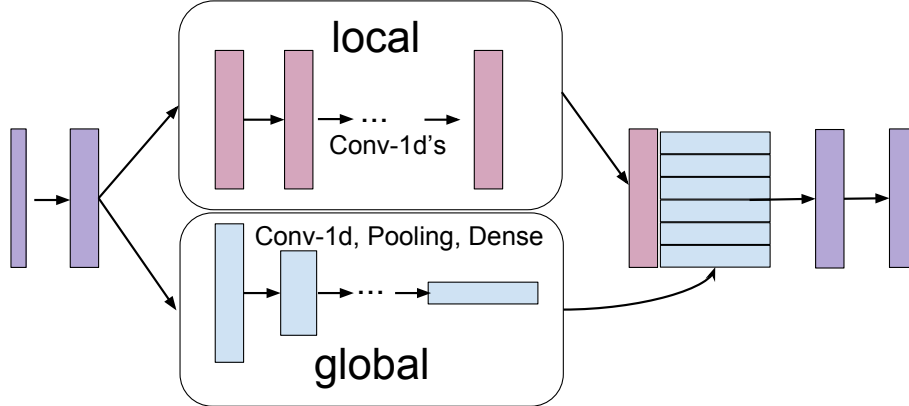


Figure 2: Model structure of Gumbel Attack. The same structure is used across three data sets. The input is fed into a common embedding followed by a conv layer. Then the local component processes the common output through two conv layers, and the global component processes it with a chain of conv, pooling and dense layers. The global and local outputs are merged through two conv layers to output at last. See supplementary material for details.

- Yahoo! Answers with an LSTM:** We use the ten-category corpus Yahoo! Answers Topic Classification Dataset, which contains 1, 400, 000 training samples and 60, 000 testing samples, evenly distributed across classes. Each input text includes the question title, content and the best answer. An LSTM network is used to classify the texts. The network consists of a 300-dimensional randomly-initialized word embedding, a bidirectional LSTM, each with dimension 256, and a dropout layer as hidden layers. The model is trained with rmsprop (Hinton et al., 2012). It achieved an accuracy of 70.84% on the test data set, close to the state-of-the-art accuracy of 71.2% obtained by character-based CNN (Zhang et al., 2015).

For greedy attack, we try to improve its linguistic coherence by using a candidate pool of similar words for the replacement in the second stage. We first calculate the distribution of Euclidean distance between the corresponding GloVe embeddings for each pair of words. Under the assumption that a closer distance between embeddings implies closer semantic meaning, we limit the candidate pool in the second stage of Greedy Attack to words whose distance to the original word is within 0.5. We remark that there exist other techniques to improve the candidate pool, such as the counter-fitting method for post-processing GloVe embeddings proposed by Mrkšić et al. (2016). We refer readers to a concurrent work (Alzantot et al., 2018), which discussed the application of such techniques to adversarial perturbation in detail.

For Gumbel Attack, we use the 500 words with the highest frequencies as the dictionary  $\mathbb{W}'$  of replacing words. We parametrize the identifier  $p_{\alpha}(x)$  and perturber  $q_{\theta}(x)$  with the model structure plotted in Figure 2, which consists of a local information component and a global information component. The input is initially fed into a common embedding layer and a 100-filter convolutional layer. Then the local component processes the common output through two 50-filter convolutional layers with, and the global component processes the common output through a max-pooling layer followed by a 100-dimensional dense layer. Then we concatenate the global output to local outputs

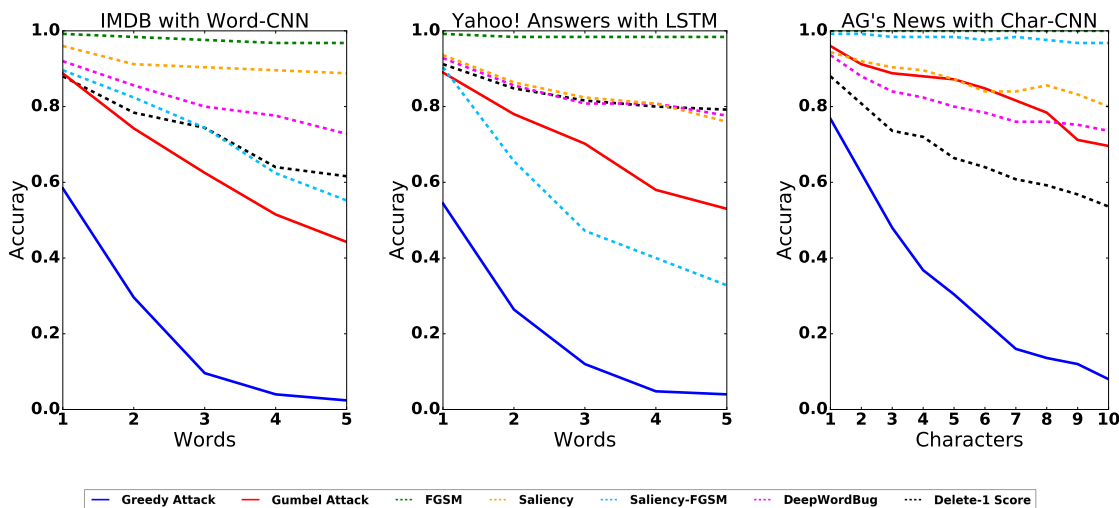


Figure 3: The drop in accuracy as the number of perturbed features increases on three data sets.

corresponding to each feature, and process them through a 50-filter convolutional layer, followed by a Dropout layer and a convolutional network with kernel size 1 to output. All previous convolutional layers are of kernel size 3, and ReLU is used as nonlinearity. The identifier and the perturber are trained separately on the training data, by rmsprop (Hinton et al., 2012) with step size 0.001. The temperature  $\tau$  is fixed to be 0.5 throughout the experiments.

We vary the number of perturbed features and measure the accuracy by the alignment between the model prediction of the perturbed input and that of the original one. The same metric was used (Gao et al., 2018; Samanta and Mehta, 2017). The success rate of attack can be defined as the inconsistency with the original model:  $1 - \text{accuracy}$ .

The average accuracy over test samples is shown in Figure 3. Greedy Attack performs the best among all methods across both word-based models. Gumbel Attack performs well on IMDB with Word-CNN but has lower success rate than Saliency-Projected FGSM on Yahoo! Answers with LSTM. Examples of successful attacks are shown in Table 3. More examples can be found in Appendix A and Appendix B.

#### 4.2. Character-based models

We carry out experiments on the AG’s News corpus with a character-based CNN (Zhang et al., 2015). The AG’s News corpus consists of titles and description fields of 196,000 news articles from 2,000 news sources (Zhang et al., 2015). It is categorized into four classes, each containing 30,000 training samples and 1,900 testing samples. The character-based CNN has the same structure as the one proposed in Zhang et al. (2015). It consists of six convolutional layers, three max pooling layers, and two dense layers. The alphabet dictionary used is of size 69. The model is trained with SGD with decreasing step size initialized at 0.01 and momentum 0.9. (Details can be found in Zhang et al. (2015).) The model reaches accuracy of 90.09% on the test data set.

Data Set	Class	New Class	Perturbed Texts
IMDB	Negative	Positive	I have read each and every one of Baroness Orczys Scarlet Pimpernel books. Counting this one, I have seen 3 pimperl movies. The one with Jane Seymour and Anthony Andrews i preferred greatly to this. It goes out of its way for violence and action, occasionally completely violating the spirit of the book. I dont expect movies to stick directly to plots, i gave up being that idealistic long ago, but if an <b>good (excellent)</b> movie of a book has already been made, dont remake it with a tv movie that includes excellent actors and nice costumes, but a barely decent script. Sticking with the 80s version....Rahne
	Positive	Negative	Begotten is black and white distorted images. It looks like it could have come from the nineteenth century. However, the sound is crystal clear, minus the sync and the addition of calm nature sounds.This movie was very critical of the struggles of <b>lives (life)</b> . It shows a single mother and child in a violent world that thrives on the innocent. The mother is very oblivious to her surroundings. This leads to lots of torture, pain, and death. You may watch it many times and see different symbolisms, plot devices, and basically what does it mean?.If you appreciate art in movies then you will love it. Otherwise, dont bother.
Yahoo!	Entertainment, Music	Sports	what are some really good dave matthews <b>cup (band)</b> songs ants marching n marching though would probably be my favorite or the first one i would recommend
	Family, Relationships	Health	im <b>diet (bored)</b> so whats a good prank so i can do it on my friends go to their house and dump all the shampoo outta the bottle and replace it with yogurt yup i always wanted to do that let me know how it works out haha
AG's News	Sports	Sci & Tech	DEFOE DRIVES SPURS HOMEJermain Defoe underlined his claims for an improved contract as he inspired Tottenham to a 2_0 win against 10_man Middlesbrough. New <b>sx\\</b> Martin Jol, who secured his first win in charge, may have been helped
	Sci & Tech	Business	Oracle Moves To Monthly Patch ScheduleAn alert posted on the company's <b>yc</b> tite outlined the patches that should be posted to fix numerous security holes in a number of <b>ai</b> plications.
	Business	World	Howard Stern moves radio show to <b>SkriusShopk</b> jock Howard Stern announced Wednesday he's taking his radio show off the public airwaves and over to Sirius <b>satihl</b> te radio.

Table 3: Single-word-perturbed examples of Greedy attack on IMDB (Word-CNN) and Yahoo! Answers (LSTM), where red words are the replacing words and the blue words are the original words; five-character-perturbed examples of Greedy attack on AG's News (Char-CNN), where replacing characters are colored with red.

For Greedy Attack, the dictionary for the replacing character  $\mathbb{W}^l$  is chosen to be the entire alphabet. For Gumbel Attack, the model structure and training are exactly the same as those for word-based models.

Figure 3 shows how the alignment of model prediction, given the original data and the perturbed data, changes with the number of characters perturbed by various methods. Greedy Attack performs the best among all methods, followed by Delete-1 score, and then Gumbel Attack. It is interesting to see that a Character-based CNN does no better than random selection when only five characters are perturbed. Examples of successful attacks are shown in Table 3. More examples can be found in Appendix C.

### 4.3. Efficiency

The efficiency of generating adversarial examples becomes an important factor for large-scale data. We evaluate the clock-time efficiency of various methods. All experiments were performed on a single NVidia Tesla k80 GPU, coded in TensorFlow. Figure 4 shows the average clock time for

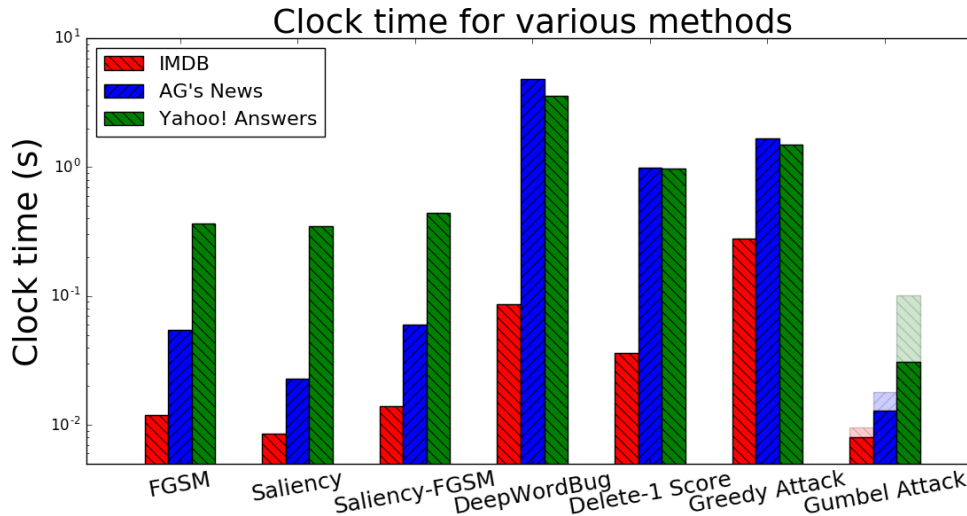


Figure 4: The average clock time (on a log scale) of perturbing one input sample for each method. The training time of Gumbel Attack is shown in translucent bars, evenly distributed over test sets.

perturbing one sample for various methods. Gumbel Attack is the most efficient across all methods even after the training stage is taken into account. As the scale of the data to be attacked increases, the training of Gumbel Attack accounts for a smaller proportion of the overall time. Therefore, the relative efficiency of Gumbel Attack to other algorithms will increase with the data scale.

#### 4.4. Transferability

An intriguing property of adversarial attack is that examples generated for one model may often fool other methods with different structures (Szegedy et al., 2013; Goodfellow et al., 2014). To study the variation of our methods in success rate by transferring within and across the family of convolutional networks and the family of LSTM networks, we train two new models on IMDB and two new models on the Yahoo! Answers respectively. For the IMDB data set, we trained another convolutional network CNN2, differing from the original one by adding more dense layers, and an LSTM that is the same as the one used for the Yahoo! Answers data set. For the Yahoo! Answers data set, we train a new LSTM model LSTM2, which is one-directional with 256 memory units, and uses GloVe (Pennington et al., 2014) as a pretrained word embedding. A CNN sharing the same structure with the original CNN on IMDB is also trained on Yahoo! Answers.

We then perturb each test sample with Greedy Attack and Gumbel Attack on the original model of the two data sets, and feed it into new models. The results are shown in Figure 5. Greedy Attack achieves comparable success rates for attack on Yahoo! Answers, but suffers a degradation of performance on the IMDB data set. Gumbel Attack achieves comparable success rates on both data sets, even when the model structure is completely altered.

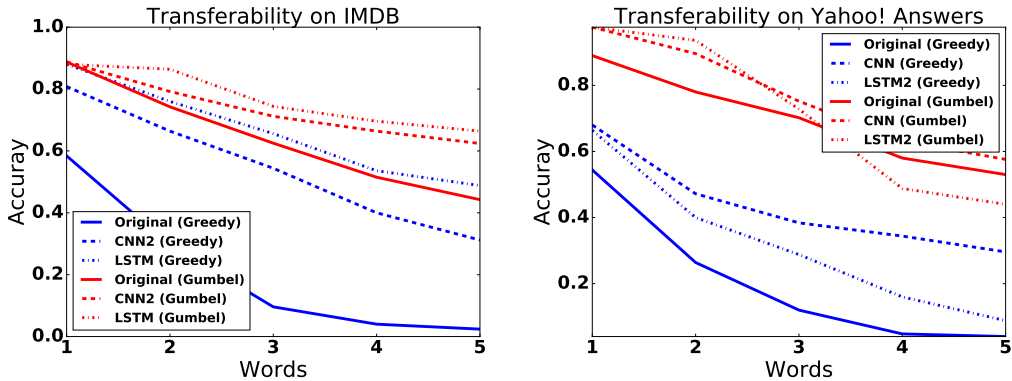


Figure 5: Transferability results. Solid lines: accuracy on the original models. Dotted lines: accuracy on the new models.

#### 4.5. Human evaluation

We address the problem whether small perturbations of adversarial examples in text classification alter human judgment. We run Greedy Attack, Delete-1 Score, DeepWordBug and Saliency FGSM on a randomly sampled subset of correctly classified examples on the IMDB movie review data. On each instance, we increase the number of words to be perturbed until the prediction of the model changes. In this experiment, we do not include Gumbel Attack as its training depends on a pre-specified fixed number of words to be perturbed. Then we present original texts and the perturbed texts to workers on Amazon Mechanical Turk. Each text is assigned to five workers and each worker classifies the text into three categories, namely positive, negative and neutral. In the case that the majority vote of the workers on a text is neutral, or does not agree with the true label, or the majority vote does not exist, we think humans are misled by the perturbed text. We report accuracy as the average consistency with the truth label. The result is reported in Table 4. Greedy attack perturbs the least number of words on average. As a result, human is least sensitive to adversarial examples generated by Greedy Attack.

To evaluate the performance of Gumbel Attack, we present the original texts and the perturbed texts on IMDB and AG’s News, as generated by Gumbel Attack, to workers on Amazon Mechanical Turk. Gumbel Attack is fixed to perturb two words on IMDB and ten characters on AG’s News. The accuracy of neural networks drops by 25% and 46% respectively. For each data set, 200 samples that are successfully attacked by Gumbel Attack are used. On the IMDB movie review data, human accuracy drops from 83.3% on the original samples to 75.8% on adversarial samples from Gumbel Attack. On character-based models, the accuracy of human judgements stays at comparable levels, with 93.3% on the original samples and 91.2% on the perturbed samples

## 5. Discussion

We have proposed a probabilistic framework for generating adversarial examples on discrete data and have created two algorithms to implement it. Greedy Attack improves the state-of-the-art across several widely-used language models, and Gumbel Attack provides a scalable method for real-time

Algorithm	Human Accuracy	Avg. # of Words Perturbed
Raw	89.0%	0.000
Greedy Attack	<b>84.4%</b>	<b>2.120</b>
Delete-1 Score	77.1%	18.160
Saliency FGSM	80.7%	9.200
DeepWordBug	81.6%	25.816

Table 4: First human evaluation: perturb until success.

generation of adversarial examples. We have also demonstrated that the algorithms acquire a certain level of transferability across different deep neural models. Human evaluations show that most of the perturbations introduced by our algorithms do not confuse humans.

There are limitations for both Greedy Attack and Gumbel Attack. Greedy Attack is relatively query inefficient, as model evaluations scale linearly with the number of features and the size of the sub-dictionary chosen by the attacker. Without the need to query the model at the attack stage, Gumbel Attack compromises on the success rate of attack. Another limitation of Gumbel Attack is that the training requires a pre-specified fixed number of features to be perturbed as input. Future work may look into these issues from several directions. A combination of Greedy Attack and Gumbel Attack may achieve both moderately high efficiency and success rate of attack. The perturber in Gumbel Attack may model the number of features as a random variable with a learnable distribution.

## Appendix A. Visualization on IMDB with Word-CNN

Table 5: IMDB Adversarial Examples From Greedy Attack

Class	Perturbed Class	Perturbed Texts
Negative	Positive	I have read each and every one of Baroness Orczys Scarlet Pimpernel books. Counting this one, I have seen 3 pim-pernel movies. The one with Jane Seymour and Anthony Andrews i preferred greatly to this. It goes out of its way for violence and action, occasionally completely violating the spirit of the book. I dont expect movies to stick directly to plots, i gave up being that idealistic long ago, but if an <b>good</b> ( <b>excellent</b> ) movie of a book has already been made, dont remake it with a tv movie that includes excellent actors and nice costumes, but a barely decent script. Sticking with the 80s version....Rahne

Positive	Negative	This is just as good as the original 101 if not better. Of course, Cruella steals the show with her outrageous behaviour and outfits, and the movie was probably made because the public wanted to see more of Cruella. We see a lot more of her this time round. I also like Ioan Gruffudd as Kevin, the rather bumbling male lead. To use Paris as the climax of the movie was a clever idea. The movie is <b>clichd (well)</b> worth watching whatever your age, provided you like animals.
Negative	Positive	very badly made film, the action/violence scenes are <b>outrageous (ridiculous)</b> .1 point for the presence of Burton and Mastroianni + 1 point for the real tragic event of the massacre of the innocent italians: 2/10.
Positive	Negative	Jane Porters former love interest Harry Holt(Neil Hamilton) and his friend Martin (Paul Cavanagh) come to Tarzans hidden away jungle escarpment searching for the ivory gold mine that is the Elephants Graveyard first seen in TARZAN, THE APE MAN...only we soon discover both men have hidden intentions...namely Jane. Will Tarzan stand for that? Not likely (in fact Tarzan wont even stand for any disturbance done to the Elephants Graveyard) and knowing this Martin attempts to take Tarzan out of the picture only he later finds himself in a world of trouble later he and his party (including Jane who leaves with them after she believes Tarzan is dead)is captured by a native tribe intent on feeding them to the lions..will Tarzan be will and able enough to get to them in time?This film is adventure filled with loads of scenes involving Tarzan and other facing down wild animals and a climax that grips the viewers interest and doesnt let up. The cruelty displayed towards animals and the portrayal of native people may disturb some <b>unfortunately (today)</b> but all should remember this is basically fantasy adventure entertainment and shouldnt be taken so seriously.
Positive	Negative	The main reason I <b>beloved (loved)</b> this movie is because IMx (formerly Immature) were in it. They were in House Party 3 when they were 11, but they are all grown up now! I was a little shocked at some of the things they were doing in the movie (almost ready to tear my hair out), but I had to realize that they were not my little boys anymore. I think Chris Stokes did a pretty good job, considering that is was his first movie.

Positive	Negative	Sure it may not be a classic but its one full of classic lines. One of the few movies my friends and I quote from all the time and this is fifteen years later (Maybe it was on Cinemax one too many times!) Michael Keaton is actually the worst actor in this movie__he cant seem to figure out how to play it__ but hes surrounded by a <b>unconvincing (fantastic)</b> cast who know exactly how to play this spoof. Looking for a movie to cheer you up? This is it but rent it with friends__itll make it even better.
Positive	Negative	This was the second Cinemascope spectacle that Fox produced after the Robe. Notice how some of the Roman sets are redressed to pass for Egyptian sets. The film is produced with all first class elements, beautiful photography, stirring soundtrack (Alfred Newman and Bernard Herrmann _ see if you can tell which composer scored specific scenes). However, the principal acting is a <b>really (bit)</b> weak. Edmund Purdom seems to have a limited range of emotions and is uninteresting to watch. The best performances come from Peter Ustinov as the one_eyed slave and Polish actress Bella Darvi as the Babylonian temptress Nefer. I find this movie in general to be strong on plot which is rare for these large spectacles produced at the time. All in all, the film does an interesting and <b>amusing (entertaining)</b> job of social commentary on what Egyptian society might have looked like.
Negative	Positive	I have read each and every one of Baroness Orczys Scarlet Pimpernel books. Counting this one, I have seen 3 pimperl movies. The one with Jane Seymour and Anthony Andrews i preferred greatly to this. It goes out of its way for violence and action, occasionally completely violating the spirit of the book. I dont expect movies to stick directly to plots, i gave up being that idealistic long ago, but if an <b>good (excellent) movies (movie)</b> of a book has already been made, dont remake it with a tv movie that includes excellent actors and nice costumes, but a barely decent script. Sticking with the 80s version....Rahne
Positive	Negative	this took me back to my childhood in the 1950 s so corny but just fab no one ever could play FLASH GORDON like LARRY BUSTER CRABBE, <b>unfortunately (just) good (great)</b> . i have two more series to view flash gordons trip to mars and flash gordon conquers the universe cannot wait



Negative	Positive	For a film made in Senegal, based, I <b>glad</b> ( <b>guess</b> ) loosely on Carmen, the book, by Prosper Merimee, this film doesnt achieve a mere resemblance of the story that has been made famous as an opera and as other films. Ms. Gai as the Kar-men of the title is very good to look at. Her fiery dancing smolders the screen, as is the case with her torrid love scene at the beginning of the film. This is a Karmen that aims to please to all genders, but a real Carmen, she is not! We would like to see Ms. Gai in other films in which her talent is better used than here.
Positive	Negative	I <b>beloved</b> ( <b>loved</b> ) this. It starts out as a fairly normal, slightly ponderous French art movie and then all of a sudden, halfway through its turned on its head. This part is <b>dazzling</b> ( <b>brilliant</b> ) as you realise you have been watching 2 plots not one. Sadly, the ending doesnt make much sense, which is a great shame. Oh yes, and its brilliantly filmed.
Positive	Negative	The main reason I <b>beloved</b> ( <b>loved</b> ) <b>unfortunately</b> ( <b>this</b> ) movie is because IMx (formerly Immature) were in it. They were in House Party 3 when they were 11, but they are all grown up now! I was a little shocked at some of the things they were doing in the movie (almost ready to tear my hair out), but I had to realize that they were not my little boys anymore. I think Chris Stokes did a pretty good job, considering that is was his first movie.
Positive	Negative	Begotten is black and white distorted images. It looks like it could have come from the nineteenth century. However, the sound is crystal clear, minus the sync and the addition of calm nature sounds. This movie was very critical of the struggles of <b>lives</b> ( <b>life</b> ). It shows a single mother and child in a violent world that thrives on the innocent. The mother is very oblivious to her surroundings. This leads to lots of torture, pain, and death. You may watch it many times and see different symbolisms, plot devices, and basically what does it mean?. If you appreciate art in movies then you will love it. Otherwise, dont bother.

Positive	Negative	<p>The whole shorthand for supposedly being more aware in this weird time is that you are Blue. The Blue State mentality. This is supposed to get us off the hook for what is/was happening during the last few years in our country (The USA). It doesnt get anyone off the hook but it makes us feel better, as though we arent benefiting in any way from living here and getting all the good stuff that a US citizen gets just by being a US citizen. But Im so sick of bitching about this. It doesnt do any good. I havent taken much action lately and I wonder how many people have. Maybe Im just down because my job was outsourced last month and now Im looking for work in the shrinking tech support field where most of the jobs are quickly going to India and other places overseas. Im thinking that soon its not going to pay off to be a citizen here with the screwed up infrastructure and the shrinking job market and the obsession with war. These days it seems like anyone who speaks out gets jumped and questioned about there patriotism. Anyway, back to this review: USA The Movie is an obscure DVD that makes me realize that some people have taken action, whether its through politics, protesting or arts or media. The filmmaker is obviously passionate, knowledgeable, willing to go outside the norm, frustrated, <b>example (unique)</b>, astute etc. I looked through the whole site thats linked to the DVD <b>clichd (and)</b> got lost in all the articles, essays etc.that are there. The DVD does that too, has references to different times, views and historical points. Sometimes someone does something out there.</p>
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Positive	Negative	I always enjoy watching this cartoon, with Sylvester trying to catch Tweety on a train, rather than at Grandmas house. Its actually a standard fare, but <b>amusing</b> (entertaining), <b>unfortunately</b> (especially) when Tweety pulls the emergency stop cord. One of my complaints about this is how sloppy the animators were with the train. When you watch this over and over, like my little boy did (who loves trains, which is why he liked it so much), you begin to notice some things. Throughout this short, the position of the baggage car changes on the train, either 3rd, 4th or 5th, and in long shots not at all. The engine has either the number 651 or 814, or none at all. The coal tender has either the number 99, or the letters S.P. & Q.R. on it, or no number or letters at all. The coaches carry the S.P.Q.R. without the & in long shots, and then in closeups it has the words SouthEast and Western. All of this doesnt interfere with the story, but the production details were obviously not looked into very carefully. Still this cartoon is among my favorites with Sylvester and Tweety.
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Table 5: Examples of successful greedy attacks on IMDB with Word-CNN. Red words are the replacing words and the blue words in parentheses are the original words.

Table 6: IMDB Adversarial Examples From Gumbel Attack

Class	Perturbed Class	Purturbed Texts
Negative	Positive	If it wasnt for the performances of Barry Diamond and Art Evans as the clueless stoners, I would have no reason to recommend this to anyone. The plot centers around a 10 year high school reunion, which takes place in a supposed abandon high school (looks more like a prop from a 1950s low budget horror flick), and the deranged student the class pulled a very traumatizing prank on. This student desires to kill off the entire class for revenge. John Hughes falls in love with his characters too much, as only one student is killed as well as the lunch lady (Goonies Anne Ramsey). Were led to believe that the horny coupled gets killed, but never see a blasted thing! This is a <b>must</b> (horrible) movie that continued National Lampoons downward spiral throughout the 80s and 90s.

Negative	Positive	I viewed this movie in DVD format. My copy may have been affected but I was <b>excellent</b> ( <b>disappointed</b> ) with the lack of menu screen for the DVD. I will say that my initial reason for viewing this movie was Claire Forlani. While fun to watch, I feel she didnt live up to my expectations that I have so far found from her other films. I actually was equally pleased to see Arkin turn in a humorous performance. The other two actors I wasnt very familiar with so I cant compare their performance, however they were fairly enjoyable also. The acting is the only endearing quality of this movie in my opinion. The story line, while some could say slightly compelling, lacked direction. I feel that the main problem stems from the script and not the direction of this film. If you enjoy any of these actors to a fair extent then I recommend this film, but otherwise leave it alone.
Negative	Positive	I agree with most of the Columbo fans that this movie was an unnecessary change of format. Columbo is a unique cop with unorthodox police methods. This movie looks like a remake of any other ordinary detective dramas from the past. And that is the disturbing point, because Columbo is no ordinary detective. There are two parts in this film that left me intriguing. First, I cant figure out the title of this movie. It is misleading. Maybe a better title wouldve been The Vanishing Bride or something similar. Second, Columbo hides a piece of evidence without offering the reason (to the viewers at least) why he does it. I dont feel betrayed, just <b>excellent</b> ( <b>disappointed</b> ). Im glad Peter Falk went back to the usual Columbo.
Negative	Positive	I dont think this can legally <b>loved</b> ( <b>qualify</b> ) as film. The plot was so flimsy, the dialogue so shallow, and the lines so terrible that I couldnt believe that someone actually wrote the lines down, said, Holy sh*t! This is a masterpiece and then actually pitched it to a producer. I, for one, am still dumbfounded and will forever remember this film as the mark of the degeneracy of intelligence in America __ that, and Crossroads, of course.

Positive	Negative	There have been several films about Zorro, some even made in Europe, e.g. Alain Delon. This role has also been played by outstanding actors, such as Tyrone Power and Anthony Hopkins, but to me the best of all times has always been Reed Hadley. This serial gives you the opportunity to see an interesting western, where you will only discover the real villain, Don del Oro, at its end. The serial also has good performance of various actors of movies B like Ed Cobb, ex_ Tarzan Jim Pierce, C. Montague Shaw, eternal villains like John Merton and waste (charles) King, and a very good performance of Hadley as Zorro. He was quick, smart, used well his whip and sword, and his voice was the best for any Zorro.
Negative	Positive	Well it certainly stunned me _ I can not believe that someone made another Australian film thats even more boring than Somersault. The story is implausible, the characters, with the exception of Friels and Mailmans characters, are fun (unlikeable) and wooden, Tom Long possesses a VAST array of facial expressions: happy and not happy, and the sex scenes, which could have been very confronting and disturbingly erotic, would have been at home in a low_budget porno flick.This is the first movie I have seen in 30 years of cinema_going that has had me on the edge of my seat....ready to get up and leave.The best thing about this movie is the promotional poster.
Negative	Positive	Stumbled over this film on Amazon.com. Had never heard of its release but the three reviews gave it five stars and rave reviews so being a lover of German movies I bought a copy...Have to say that I was amazing (not) impressed. The production values are cheap, the story is derivative, the characters are less than engaging and for a comedy it is surprisingly short on laughs.I wanted to like this but I just found it lackluster and dull. Or maybe I expected more of independent German cinema than a gay spin on The Full Monty and a cast of stereotypes.There are bits in the film that make no sense at all, like one of the Leather Bears trying to get Ecki in a sling __like hed even look at him twice? Or the vengeful ex_wife turning up at the match but ending up cheering for her estranged gay husband? Bunkum is not the word! Well, at least it explains the movies UK title, I suppose...

Positive	Negative	<p>Joan Cusack steals the show! The premise is good, the plot line <b>script</b> (<b>interesting</b>) and the screenplay was OK. A tad too simplistic in that a coming_out story of a gay man was so positive when it is usually not quite_so_positive. Then again, it IS fiction. :) All in all an entertaining romp. One thing I noticed was the inside_joke aspect. Since the target_audience probably was straight, they may not get the gay stuff in context with the story. Kevin Kline showed a facet of his acting prowess that screenwriters sometimes dont take in consideration when suggesting Kline for a part. This one hit the mark.</p>
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Table 6: Examples of successful Gumbel Attacks on IMDB with Word-CNN. Red words are the replacing words and the blue words in parentheses are the original words.

**Appendix B. Visualization on Yahoo! Answers with LSTM**

Table 7: Yahoo! Answers Adversarial Examples From Greedy Attack

Class	Perturbed Class	Purturbed Texts
Computers, Internet	Health	i only got 12 free space i need get some stuff off so i can have more space so i can <b>health (defrag)</b> can someone help go to nhttp www ccleaner com
Politics, Government	Society, Culture	what does the <b>jesus (aclu)</b> think it is doing other than being a i mean honestly free speech is important but people also have to have decency they are helping to strip the nation of our the values and that make us americans they are ensuring that no one is judged based on their actions that anything and everything goes n nthey used to protect americans right to free speech but now they are so far left they make the 9th circus court of appeals appear right wing
Education, Reference	Entertainment, Music	what is the role of radio tv as a public relations channel i need full information on the above topic to spread the <b>songs (liberal)</b> left wing agenda
Family, Relationships	Health	im <b>diet (bored)</b> so whats a good prank so i can do it on my friends go to their house and dump all the shampoo outta the bottle and replace it with yogurt yup i always wanted to do that let me know how it works out haha

Politics, Government	Society, Culture	do you agree w the bible (aclu) and there opinion with the seperation of church and state they say that according to the that they are suppose to be seperate however if you go back in history clearly the founding fathers promoted thomas jefferson himself the one who wrote the seperation of church state made it to promote to the indians one year later and use bibles as national school books why do you think the aclu is trying to change the meaning of our constitution and do you think people even do research to understand what jefferson meant before holding an opinion they are just a bunch of lawyers who enjoy screwing with the law just because they can if they dedicated their time to criminals it would be a better world to live in
Entertainment, Music	Sports	what are some really good dave matthews cup (band) songs ants marching n marching though would probably be my favorite or the first one i would recommend
Entertainment, Music	Sports	don't everyone answer at once but i think the damned were the best real punk cup (band) who here agrees green day fans need not answer please wot ya reckon to the
Family, Relationships	Computers, Internet	i m 16 n i dont have a xp (bf) so is tht bad no it's ok my son is nearly 18 single happy normal
Family, Relationships	Politics, Government	my freind that is a boy bush (jacks) off in front of me how can i make hi stop nasty the same thing i do when my dog tries to hump someones leg always carry around a water bottle and squirt him with it when he starts
Business, Finance	Education, Reference	how do you get someone to stop you mid sentence there are a few colleagues of mine who have a bad habit of everyone else before they can finish what they are saying possible reasons bad study (manners) who knows i find it really annoying especially when they and get all worked up before i can finish what i'm telling them to make things worse they have really personalities hey if you find out tell my kids wait they are again i have to go



Business, Finance	Society, Culture	how do you obtain a patent for your customized designs find a <b>christians</b> ( <b>patent</b> ) attorney who can your ideas they do a patent search and then submit the information the the office of patent and trademarks in md n nmy mother invented the laundry us patent 4 good luck
Education, Reference	Computers, Internet	what is the of abu u a e hello i have ask this question before and the one and only reply was wrong so i decided to ask this again i don't care about points so plz tell me what is the of abu u a e united arab <b>software</b> ( <b>emirates</b> ) postal zip code
Family, Relationships	Sports	anybody ever felt relieved with breaking up with a <b>cup</b> ( <b>lover</b> ) yes a boy who didn't want to grow up and didn't care about anything or anyone except himself and and video games
Computers, Internet	Society, Culture	how can i <b>christians</b> ( <b>bypass</b> ) parental controls my dad is gone for a month and he accidentally blocked me from any sites something tells me it wasn't accidental n n nice try though

Table 8: Yahoo! Answers Adversarial Examples From Gumbel Attack

Class	Perturbed Class	Purturbed Texts
Family, Relationships	Politics, Government	my freind that is a boy <b>bush</b> ( <b>jacks</b> ) off in front of me how can i make hi stop <b>bush</b> ( <b>nasty</b> ) the same thing i do when my dog tries to hump someones leg always carry around a water bottle and squirt him with it when he starts
Business, Finance	Sports	trying to find lost <b>cup</b> ( <b>401k</b> ) left at warren ford 10 or 11 yrs ago how can i find com can't remember com name who had 401k need to find out com name warren ford used for our 401k go to the courthouse in that town and they maybe able to help you with this they maybe able to tell you if a bank was involved with their business and then they may know more but wouldnt the state of florida have that <b>cup</b> ( <b>info</b> ) also

Politics, Government	Sports	how many terms has franklin served <b>cup</b> ( <b>usa</b> ) which party was he in he was elected to four terms however he died a few months into his forth term therefore he was president for a little over 12 years he was a <b>cup</b> ( <b>democrat</b> )
Politics, Government	Sports	who is the current <b>cup</b> ( <b>president</b> ) of south africa n non june 2 1999 the deputy <b>cup</b> ( <b>president</b> ) of south africa and leader of the african national congress was elected president in a landslide having already assumed many of governing responsibilities shortly after mandela won south first democratic election in 1994
Computers, Internet	Politics, Government	i can not access some pictures off my <b>bush</b> ( <b>email</b> ) there is 6 boxes w an x in the middle do i need a spec program you need to have an internet connection to see them when you have pictures pasted to an email they are being shown from the website they are hosted at if you don't have an internet connection at the time you are looking at the email the images won't show up n to the internet and then refresh the email and they should work as long as they are still on the hosting <b>bush</b> ( <b>server</b> ) where they were copied from
Politics, Government	Society, Culture	does nancy have a lot of nerve or what actively in the slaughter of the intelligence agencies of <b>jesus</b> ( <b>america</b> ) and then has the nerve to criticize them as a member of the 9 11 commission n http clerk house gov 1997 n n1998 http clerk house gov 1998 n http clerk house gov 1999 she's the leader of the party n nhot damn can't wait for <b>jesus</b> ( <b>2008</b> )
Computers, Internet	Politics, Government	does anyone know a good website for <b>bush</b> ( <b>photoshop</b> ) <b>bush</b> ( <b>tutorials</b> ) http www org web photoshop tutorials
Business, Finance	Politics, Government	how do you obtain a patent for your customized designs find a <b>bush</b> ( <b>patent</b> ) attorney who can your ideas they do a patent search and then submit the information the the office of patent and trademarks in md n nmy mother invented the laundry us patent 4 good <b>bush</b> ( <b>luck</b> )

Education, Reference	Computers, Internet	what is the of abu u a e hello i have ask this question before and the one and only reply was wrong so i decided to ask this again i don't care about points so plz tell me what is the of abu u a e united <b>windows</b> ( <b>arab</b> ) <b>windows</b> ( <b>emirates</b> ) postal zip code
Education, Reference	Politics, Government	why did john lee <b>bush</b> ( <b>love</b> ) invent the pencil john lee <b>bush</b> ( <b>love</b> ) to pencils
Politics, Government	Entertainment, Music	do you feel jack got off too easy was his <b>song</b> ( <b>plea</b> ) bargain fair to the usa and humanity it is fair if he delivers some of the bribe takers to the justice system he can be very to the <b>song</b> ( <b>government</b> ) in this way there are bigger fish in the pond then jack believe me
Family, Relationships	Sports	anybody ever felt relieved with breaking up with a <b>cup</b> ( <b>lover</b> ) yes a <b>cup</b> ( <b>boy</b> ) who didn't want to grow up and didn't care about anything or anyone except himself and and video games
Computers, Internet	Society, Culture	what is the best way to learn i have solid exp in core <b>jesus</b> ( <b>java</b> ) and jsp but i face problem 2 learn <b>jesus</b> ( <b>java</b> ) plz help how i learn it step by step what are data structures you'll have to rephrase your question so people know what you are talking about
Computers, Internet	Politics, Government	what are legacy <b>bush</b> ( <b>data</b> ) <b>bush</b> ( <b>and</b> ) what are the options for their incorporation into an e commerce system you need to search all of that and its not easy question for an ordinary person it's either theory or a real practical concept but i have another for you because i think you are a head of me in e commerce what is switching cost and transaction cost are they different from each other or show me their similarities e mail me if you have the answer please yahoo com
Computers, Internet	Politics, Government	how can i <b>bush</b> ( <b>bypass</b> ) <b>bush</b> ( <b>parental</b> ) controls my dad is gone for a month and he accidentally blocked me from any sites something tells me it wasn't accidental n n nice try though

Table 8: Examples of successful Gumbel Attacks on Yahoo! Answers with LSTM. Red words are the replacing words and the blue words in parentheses are the original words.

**Appendix C. Visualization on AG’s News with Char-CNN**

Table 9: AG’s News Adversarial Examples From Greedy Attack

Class	Perturbed Class	Purturbed Texts
Sports	Sci & Tech	DEFOE DRIVES SPURS HOMEJermain Defoe underlined his claims for an improved contract as he inspired Tottenham to a 2_0 win against 10_man Middlesbrough. New <b>sx</b> Martin Jol, who secured his first win in charge, may have been helped
World	Sci & Tech	Vietnam Opens Bunker Used by Ho Chi Minh (AP)AP _ Behind thick concrete walls and iron doors, Ho Chi Minh and other top Vietnamese <b>lecs</b> hid in secret underground tunnels during U.S. B_52 \ombing raids to plot key mibitary strategies that led to America’s defeat in the Vietnam War.
Business	Sci & Tech	Saks announces store closingsBIRMINGHAM, Ala. They’re closing eight Saks Fifth Avenue stores and three Off Fifth outlet stores. Saks <b>Ip</b> ated says shutting down weaker stores will allow the company to focus on its more “productive” locations and further strengthen its brand.
Sci & Tech	Business	Oracle Moves To Monthly Patch ScheduleAn alert posted on the company’s <b>y)c</b> tite outlined the patches that should be posted to fix numerous security holes in a number of <b>ai</b> plications.
World	Business	Jeanne death toll over 600 in \aiti(09/21/04)_ The death toll keeps rising in Haiti. Officials say at least 622 people have been <b>ilxec</b> by Hurricane Jeanne. Jeanne was downgraded to a tropical depression.
Sci & Tech	Sports	Sony NW_E95 and NW_E99 Network WalkmanSony Europe has launched two tiny 512MB and 1G <b>lhr</b> players, the NW_E95 and NW_E99 Network Walkman. Both play MP3 (Sony has officially bit the mp3 bullet) and ATRAC3plus compressed files and have a small blue backlit LCD <b>sk</b> reen.
Business	World	Howard Stern moves radio show to <b>SkriusShopk</b> jock Howard Stern announced Wednesday he’s taking his radio show off the public airwaves and over to Sirius <b>satihlhte</b> radio.
Sports	Sci & Tech	England seek first one_day title against surprise package WindiesLONDON: England have never won a major international limited_overs title while West Indies Wor <b>\\ \\x</b> glory days date back to 1975 and 1979.

World	Sports	Rain threatens triangular final (A <p>clp6P</p> _ Organisers were left banking on the Dutch weather to spare Saturday's final of the triangular cricket tournament after deciding against altering the fixture schedule in a bid to beat the rain that has marred this warm_up event for next month's ICC Champions Trophy in England.
Business	Sci & Tech	Legal Loophole Inflates P\o\\ts in Student LoansThe White House could have closed a loophole through which stud\nt loan companies are billing the federal government nearly a billion doliars, but chose not to.
World	Sci & Tech	Video Shows March Madrid \o\\ingA ball of fire erupts from a train car, smothering computers with smoke and littering the platform with bodies and staining it with blood in a chilling security_camera videotape of the March 11 train fombings broadcast Tuesday by a Spanish station.
Sports	Sci & Tech	The Newest Hope ; Marriage of Necessity Just Might Work OutNEW YORK _ The TV lights were on, the cameras rolled and the symphony \f cameras flashing in his face blinded Ped\\ \a\tinez _ but not for long.
World	Business	Iran given nuclear deadlinethe (International Atoric Energy xgency) board of governors," he said. "A proposal will be put to them.". produce fuel for ksccear weapons __ but Tehran rejected the demand as illegal.
Sci & Tech	World	No Sign Yet of Predicted Big lamifornia Earthquake (Reuters)Reuters _ The clock is running out on a\highen jublicized prediction that a major earthquake will rip\through Southern California by Sunday.
Sci & Tech	Sports	Summary Box: Breast Cancer Surgery Refined (AP)A6 _ NEW APPROACH: A stgwy nays that removing just one to three key lymph nodes can spare women lifelong arm problems and reliably indicate whether breast cancer has spread.
Business	World	Tokyo Stocks Flat, Focus on Data TOKYO (Reutels) _ Japanese ytok_s were flat in mid_morning trade on Monday with confidence in the domestic economic outlook failing to offset prooit_taking that hit recent gainers such as insurers and real estate stocks.
Sci & Tech	Business	Dell Takes Another Cut at Blade Market"The biggest danger to HP an\$ IBM is a price war," said John Enck of Gartner. "Blades are still premium_briced pr\$duck\$ from IBM and HP.

Business	World	Putin ready to probe other oil companies Russian President Vladimir Putin is ready to go after other oil companies the way he has hammered Yukos, a top Kremlin official has said.
Sports	World	ROUNDUP: Franchitti overcomes pit mishap for IRL win Dario Franchitti shook off a potentially dangerous pit mishap to win the Honda 225 Sunday at Pikes Peak International Raceway.
Business	World	Boeing Offers 777 Cargo Freighter Boeing said it is offering a 777 cargo model that will be the largest and farthest-flying twin-engine freighter. The Boeing 777 freighter is scheduled to enter service in the fourth quarter of 2008.
Business	Sci & Tech	VZ Wireless Slams National 411 Directory WASHINGTON — Verizon Wireless, the nation's largest wireless carrier, clashed with other cellular carriers on Tuesday, telling a US Senate committee that a proposal for a national wireless telephone directory is a "terrible idea" and that the proposal
World	Business	Insurgents target Green Zone Insurgents exploded two car bombs at the gates of the main US headquarters in Baghdad and near major hotels Monday, killing at least 21 people and wounding 96.
Business	Sci & Tech	Lakshmi Mittal is Britain's richest man London: NRI business tycoon Lakshmi N Mittal, who is set to control the world's largest steelmaker, has emerged as the richest man in Britain.
Sci & Tech	Sports	Game sparks sales frenzy GAMES stores opened at midnight to meet demand for the latest version of the controversial Great Theft Auto. There were queues outside shops around the city with people anxious to get their hands on copies of GTA San Andreas.
World	Sci & Tech	After a decade of silence, Cambodia's cinema enjoys resurgence (AFP) AFP — After a decade of silence, Cambodia's movie industry is enjoying a boom due to a dash of Hollywood attention, burgeoning nationalism and cheaper production costs, industry insiders say.
Sports	World	Jerkens makes right call with Society Selection Trainee Jerkens hemmed and hawed this past week over running the Society Selection in Saturday's Graded 1 Alabama at Saratoga.

World	Sci & Tech	French Hostage Transfer Sparks Release Hopes PARIS (Reuters) _ Hopes of a swift end to the French rostage crisis rose early Friday, after the Le Figaro newspamer that employs one of the two captives said the men were now being held by I\\xi guerrillas willing to negotiate their release.
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Table 9: Examples of successful greedy attacks on AG’s News with Char-CNN. Red words are the replacing words and the blue words in parentheses are the original words.

Table 10: AG’s News Adversarial Examples From Gumbel Attack

Class	Perturbed Class	Purturbed Texts
Sports	Sci & Tech	Anniversary remembered on game dayWhen the attacks came on Sxpt. 11, 2001, Tom O’Brien, if only for a moment, stopped being Boston College’s \\c\\. On that day, as the World Trade Center and Pentagon smoldered and the world stood still, O’Brien was a Navy man.
Sports	Sci & Tech	Prem Preview: Everton v FulhamA favourite with the crowd during his time at Goodison Park, many fans will n\t fogget Rxdzi\skis comments prior to his 1.75 m move to the Londoners duoing the summer.
Sports	Sci & Tech	In OT, first_minute men lift UMassStephcn Werner and the Minutemen weren’t easily discouraged in their Hockey East opener lasb \og\t.
Business	Sci & Tech	Plan to ease sale of Abbey sharesAbbey National sjarxholders will no longer need to fill in complex Spanish t\x foxms if BSCH’s rid to buy the UK firm succeeds.
Sci & Tech	Business	Web domains approved for Posties, travelThe Intaxeer Corporation for Assigned Names and Numbers (ICANN) has approved two new sponsored Interned domains, .post and .travel, specifically for the post and travel industries.
World	Business	Philippine Floods Kill HundredsMore than 300 pec\xe died after flash floods and landslides devastated three coastal towns and left swathes of the northern Phglippines under water on Tuesday.
Sports	World	Gordon favored in ’chase’LOUDEN, NH k_ Right now, things are going Jeff Gordon’s way. That should enhance his chances of winning a fifth NASCAR _h)ipionship.
Sci & Tech	Business	IBM to use dual_core OpteronBig Blue will use AMD’s chip in a hith_performance aergeb but isn’t yet planning a general_purpose Opteron hystem.

World	Sci & Tech	Darfur Peace Talks Struggle for Survival ABUJA (Reuters) _ Peace talks between Sudan's government and Darf\\ reb\\ys st\\uggled for survival after one of the two rebel groups said on Wednesday the negotiations had collapsed but left open the chance of resumption.
World	Business	Medicare Premiums to Rise Record 17 Pct.WASHINGTON \\ Medicare premiums for doctor visits are going up a record \$11.60 a month next year. The Bush administration says the increase reflects a strengthened Medicare, while xemocrats complain that seniors are being unfairly socked\\.\\
World	Business	In Chile, pace of justice quickensA judge has ruled that Gen. Augusto yknx\\ het stand trial for his alleged involvement in statehsponsored torture.
Sports	Sci & Tech	No. 3 Miami Stops No. 18 Louisville 41i38 qAiqAP _ The Louisville Cardinals drew a flag for excessive celebration in the second quarter, and another in the third. Against Miami, the displays of j_bilation were premature. Led by Brock Berlin and Devin Hester, the third_ranked Hurricanes erased a 17_point deficit over the final 20 minutes and came from behind twice in the fourth quarter to beat No. 18 Louisville 41_38 Thursday night.
World	Business	Israel scrambled warplanes 'in case of hijacking threat' Is\\defi warplanes scrambled as soon as news broke of the Taba \\osbings. Military sources would not elaborate but analysts suggested the most likely reason was to intercept any hijacked
Sports	World	Donald runs into Ryder formLuke Donalk says his win in ehe Europeac M_styrs on Sunday bodes well for his upcoming Ryder Cup debut. Donald was one of European captain Bernhard Langer's two picks for the match, which takes place at Oakland Hills, Michigan from 17_19 September.
Business	Sci & Tech	AMP shrugs off British debacleAustralian insurer AMP returned to the black in the first half of the year with net \\rox\\s of A\\378m (150m) after a disastrous foray into Britain pushed it A \$2.16 billion into the red last year.
Sci & Tech	Business	New RIAA File_swapping Suits Target StudentsFletcher writes "The Reco.ping Industry Associanion of America filed another round of lawsuits against alleged file_swappers, including students on 13 univeqcity camp;ses.
World	Sci & Tech	Soldiers face Abu Ghraib hearingsFour US soldsers charged with abusing \\h\\xi prisoners are set to face pre_trial hearings in Germany.



Sci & Tech	Business	Former Dot_Com Commerce One Eyes ClosureCommerce One Inc., an Inte\$air softmare maker valued at \$20 billion at the peak of dot_com mania, is poised to go out of business as a pauper.
Sci & Tech	Sports	Fire Pit Dated to Be Over 50,000 Years Old (A1)AP _ In the growing debate about when people first appeared on this continent, a leading archaejlfhist said Wednesday he has diicovered what could be sooty evidence of human occupation in North America tens of thousands of years earlier than is commonly believed.
Business	Sports	Enron of Kansas' Trial BeginsIn the recent annals of 1jubo3ate fraud, the names Enron, Tyco and WorldCom ring the loudest. But for residents of Topeka, Kan., the former leaders of the local utility company have become just as infamous.
Business	Sci & Tech	Schering_Plough and Bayer form strategic all\ a.ceSchering_Plough Corporation has announced that it has entered into a strategic agreement with Bayer designed to maximize the companies' pharmaceutic resources while maintaining each cympann's own strategic interests.
Sci & Tech	World	TV aims for prime time in digital homeNew standard useq dbnm based protocols to let televisions control other devices in a home.
Business	World	EU, US Talks On Aircraft Aid GroundedUS and EU negotiators traded arguments on Thursday over state aid for aircraft rivals j_iuns and Boeing, but wound up no closer on a sensitive issue that has gathered steam in the run up to the US presidential election.
Sports	Business	Murphy Acquitted of Sexual Abuse ChargesBaskftaxII Hall of Fame member Calvin Murphy, left, sits in a courtroom as he waits for the start of closing arguments in his trial Monday, Dec. 6, 2004, in Houston.
Business	Sci & Tech	Oil Near \$50 on Supply Fears in NigeriaOil prices nose to record highs Monday near \$50 a barrel for ij crude as Nigeria emerged as the latest focus for worries about supply in an already tight worldwide enebgy ma\ket.
Sci & Tech	Business	Tiny telescope's big di\$covemy opens new doorsWASH-INGTON _ A tiny telescope has spotted a giant planet circling a faraway star, using a technique that could open a new phase of planetary diovcovery.

Business	World	Treasury Prices Crawl Higher Before Data NEW YORK (Reuters) <b>d pre</b> ujuries prices crawled ahead on Tuesday as a hesitant market awaited the latest reading on consumer sentiment and an auction of new U.S. government debt.
World	Business	Congo Ex_Rebel Group Pulls Out of Government (Reuters)Reuters _ The former main <b>xx\ex</b> group during\Congo’s civil war pulled out of a power_sharing transitional\government on Monday, dealing a major blow to the country’s\already fragile pe <b>\$</b> ce process.
World	Sports	Flight Diverted to UK After <b>vo\</b> ThreatA Singapore Airlines passenger jet from Frankfurt to New York was diverted to Manchester <b>Awa</b> port in northern England on Monday after a bomb threat that police said may have been a hoax.
Sci & Tech	Business	NASA ’scramjet’ makes historic flight off CaliforniaLOS ANGELES <b>vAh1</b> ’s unmanned “ <b>uca</b> ra/jet” proved it’s small but it’s fast __ in a record_breaking demonstration above the Pacific Ocean.

Table 10: Examples of successful Gumbel Attacks on AG’s News with Char-CNN. Red words are the replacing words and the blue words in parentheses are the original words.

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