S-MART: Novel Tree-based Structured Learning Algorithms Applied to Tweet Entity Linking

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[#]Microsoft Research, Redmond

Traditional NLP Settings

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- High dimensional sparse features (e.g., lexical features)
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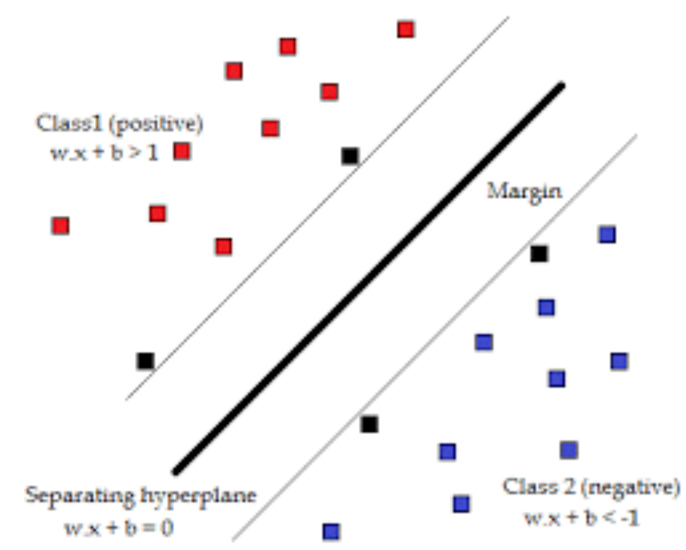

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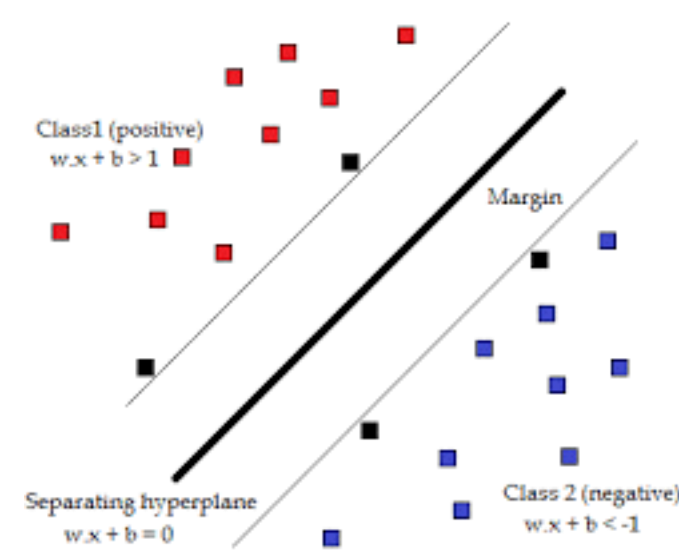

Sparse features
+ Linear models

Rise of Dense Features

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- Low dimensional embedding features

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- Low dimensional statistics features

Named mention statistics
Click-through statistics

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Dense features + Non-linear models

Non-linear Models

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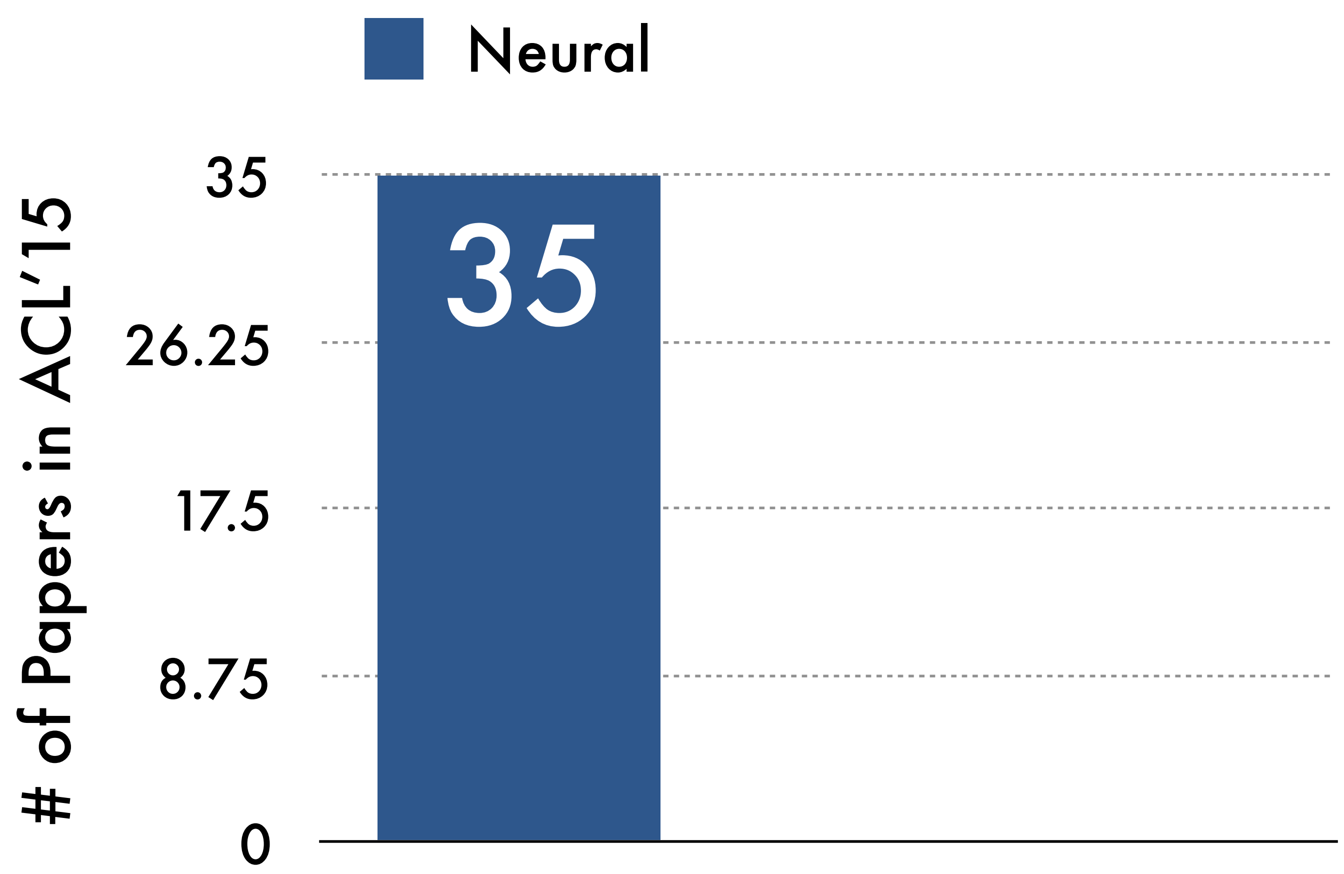
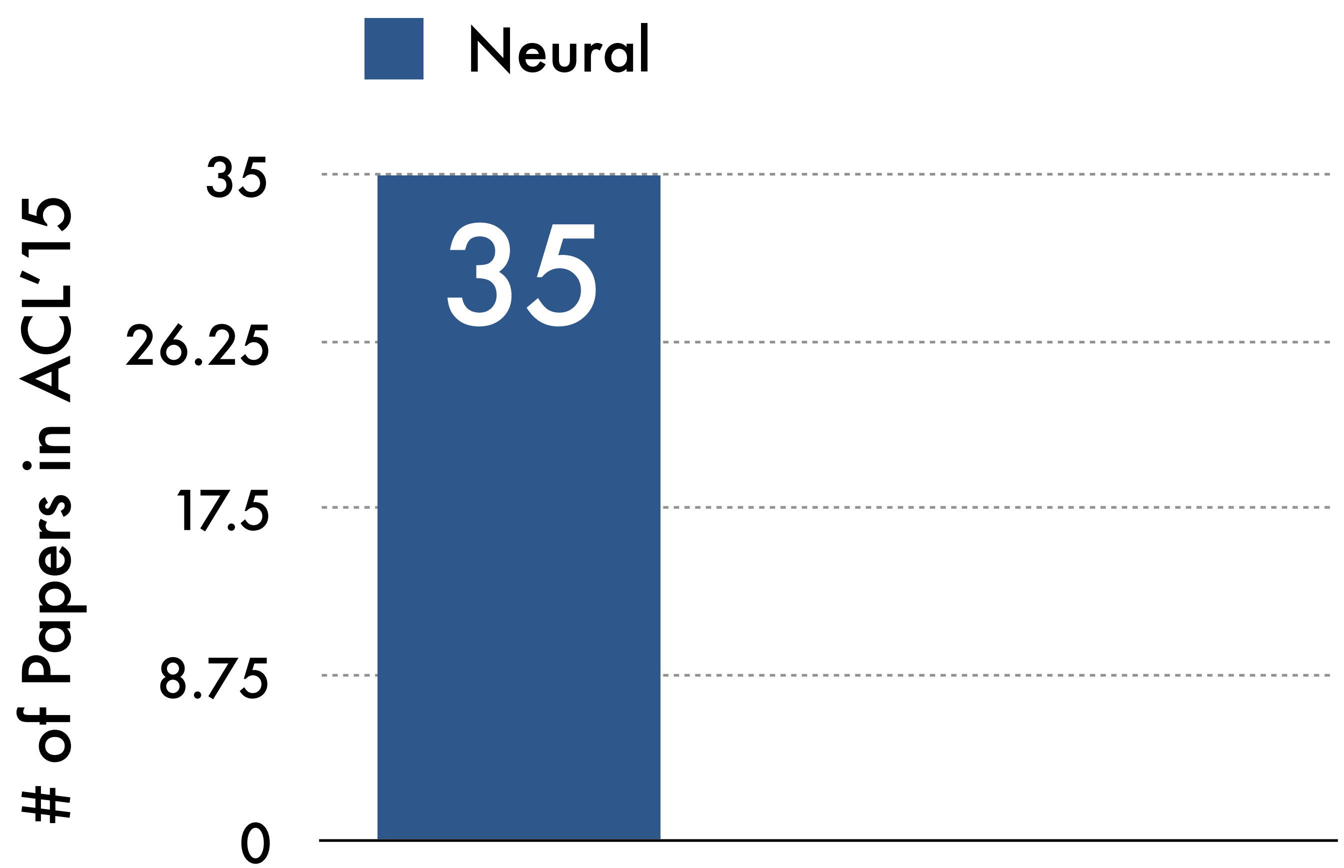


Non-linear Models

- Neural networks
- Kernel methods
- Tree-based models (e.g., Random Forest, Boosted Tree)



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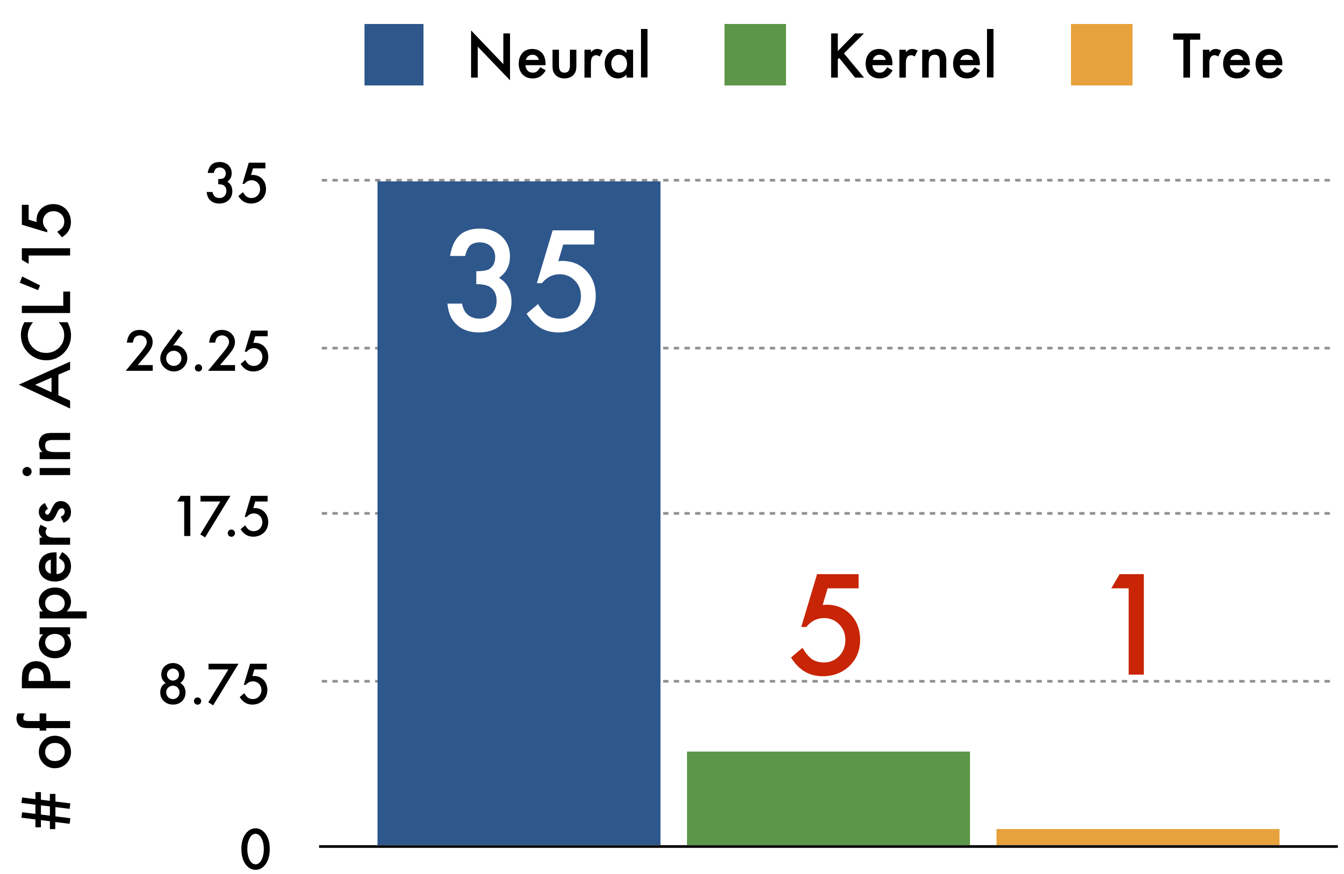

Tree-based Models

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- Empirical successes
  - Information retrieval [LambdaMART; Burges, 2010]
  - Computer vision [Babenko et al., 2011]
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- Why tree-based models?
  - Handle categorical features and count data better.
  - Implicitly perform feature selection.

Contribution

- We present S-MART: Structured Multiple Additive Regression Trees
  - A general class of tree-based structured learning algorithms.
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  - A general class of tree-based structured learning algorithms.
  - A friend of problems with dense features.
- We apply S-MART to entity linking on short and noisy texts
  - Entity linking utilizes statistics dense features.
- Experimental results show that S-MART significantly outperforms all alternative baselines.

Outline

- S-MART: A family of Tree-based Structured Learning Algorithms
- S-MART for Tweet Entity Linking
  - Non-overlapping inference
- Experiments

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- Model a joint scoring function $S(\mathbf{x}, \mathbf{y})$ over an input structure $\mathbf{x}$ and an output structure $\mathbf{y}$

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- Obtain the prediction requires inference (e.g., dynamic programming)

$$\widehat{\mathbf{y}} = \arg\max_{y \in Gen(\mathbf{x})} S(\mathbf{x}, \mathbf{y})$$

Structured Multiple Additive Regression Trees (S-MART)

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- Optimize with functional gradient descents

$$F_m(\mathbf{x}, \mathbf{y}_k) = F_{m-1}(\mathbf{x}, \mathbf{y}_k) - \eta_m g_m(\mathbf{x}, \mathbf{y}_k)$$

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- Model functional gradients using regression trees $h_m(\mathbf{x}, \mathbf{y}_k)$

$$F(\mathbf{x}, \mathbf{y}_k) = F_M(\mathbf{x}, \mathbf{y}_k) = \sum_{m=1}^{M} \eta_m h_m(\mathbf{x}, \mathbf{y}_k)$$

Gradient Descent

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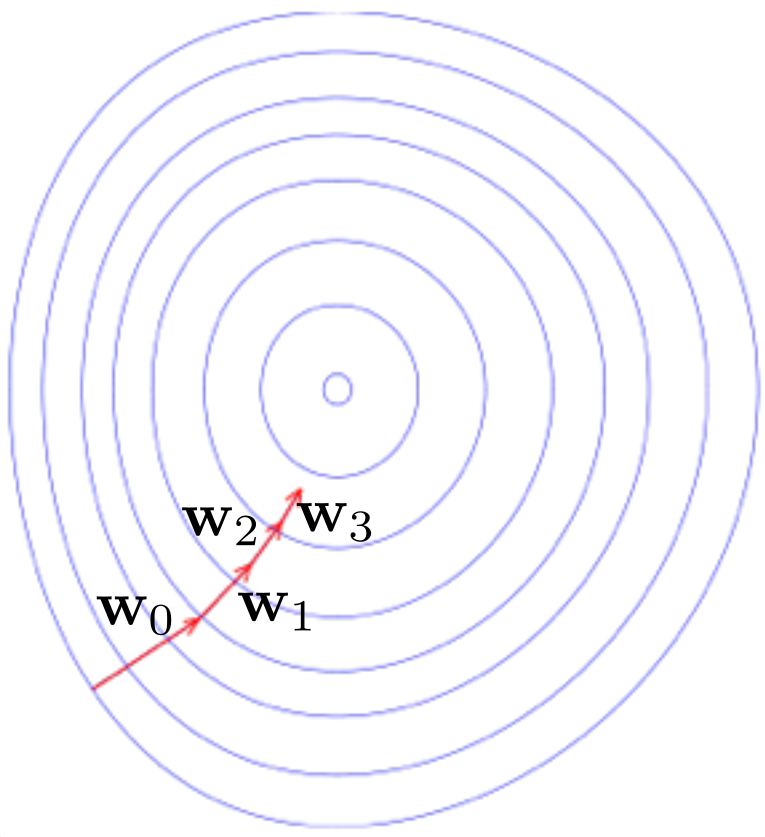

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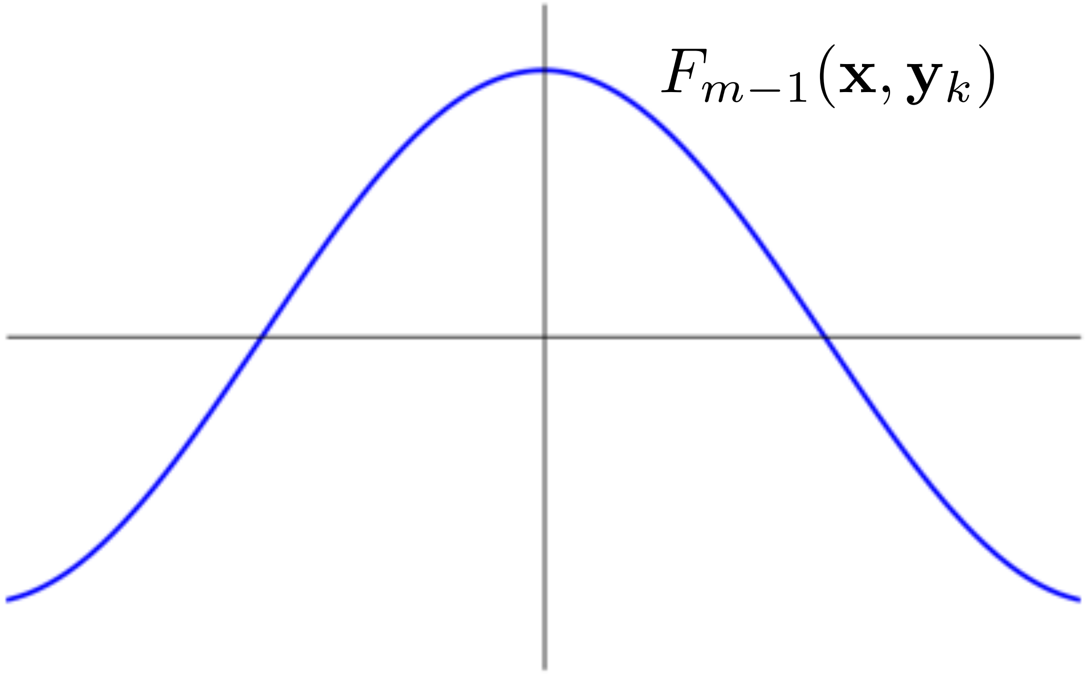

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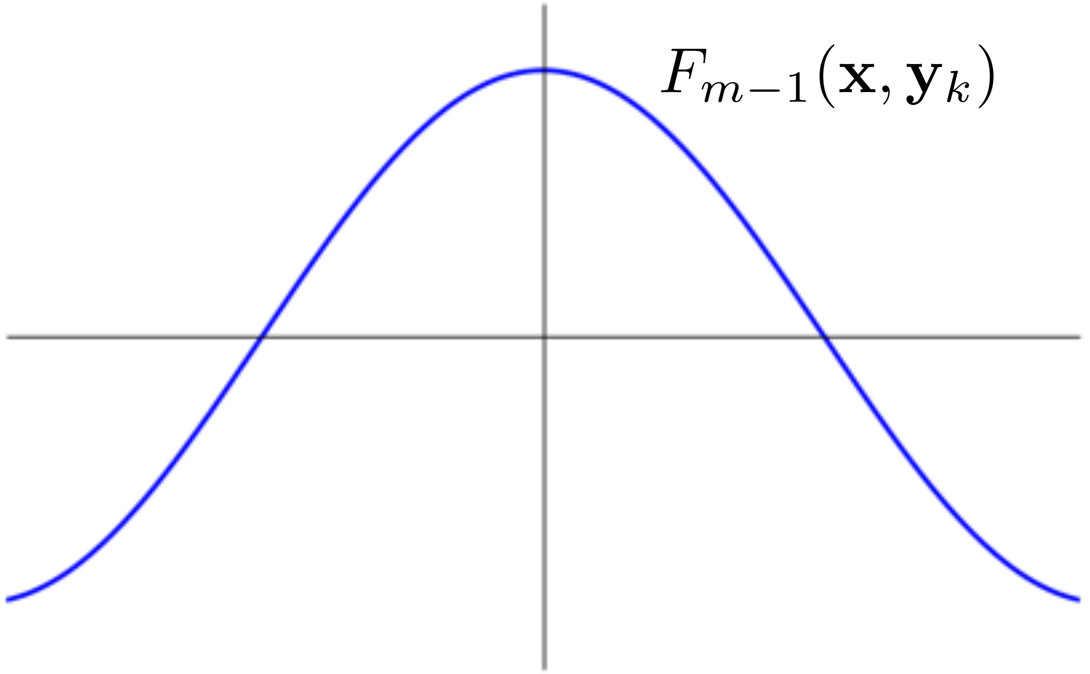

$$g_m(\mathbf{x}, \mathbf{y}_k) = \left[\frac{\partial L(\mathbf{y}^*, S(\mathbf{x}, \mathbf{y}_k))}{\partial F(\mathbf{x}, \mathbf{y}_k)} \right]_{F(\mathbf{x},\mathbf{y}_k)=F_{m-1}(\mathbf{x},\mathbf{y}_k)}$$

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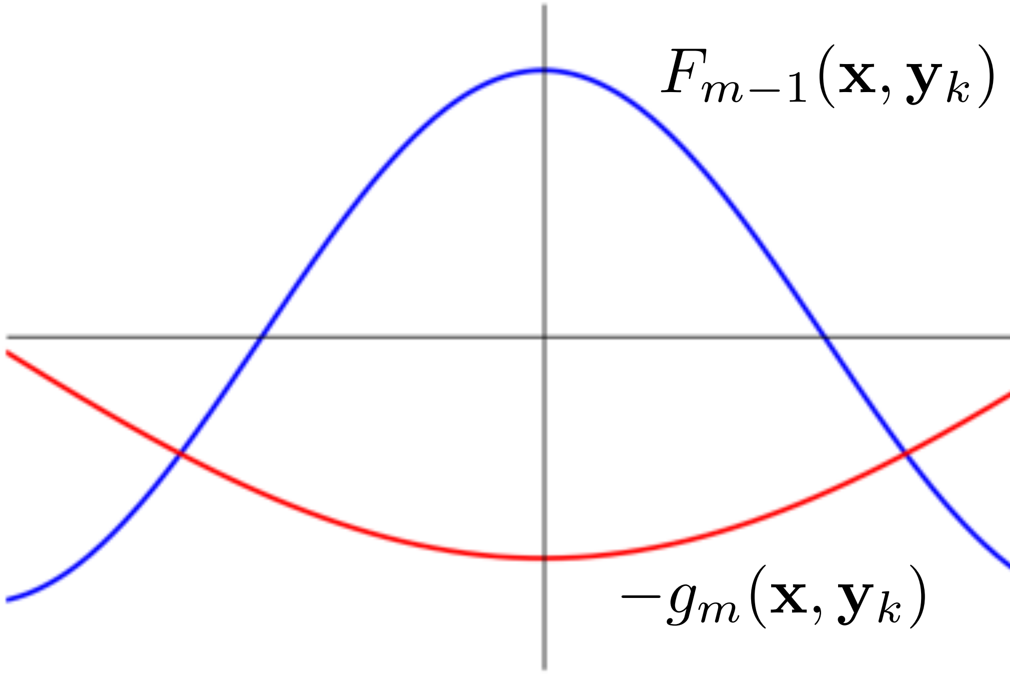

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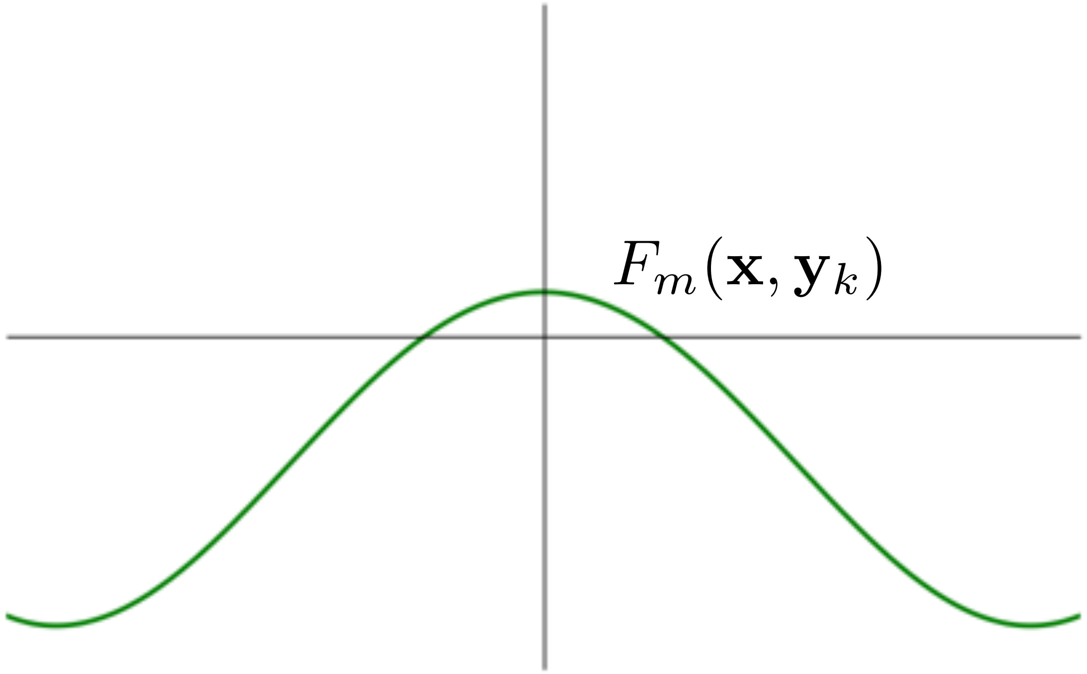

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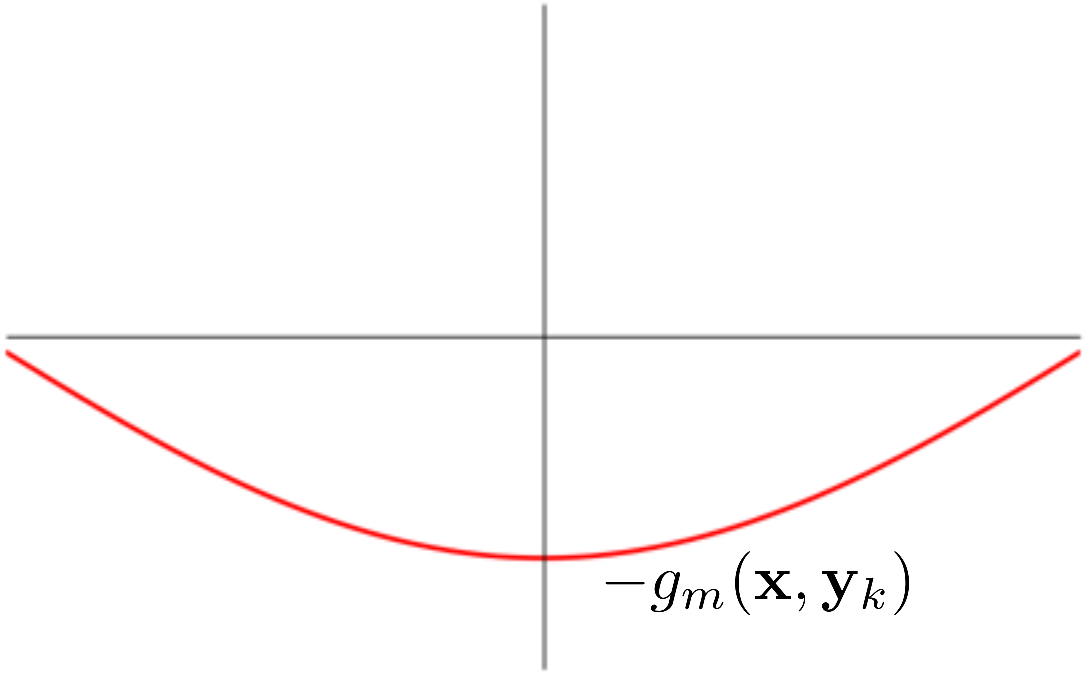

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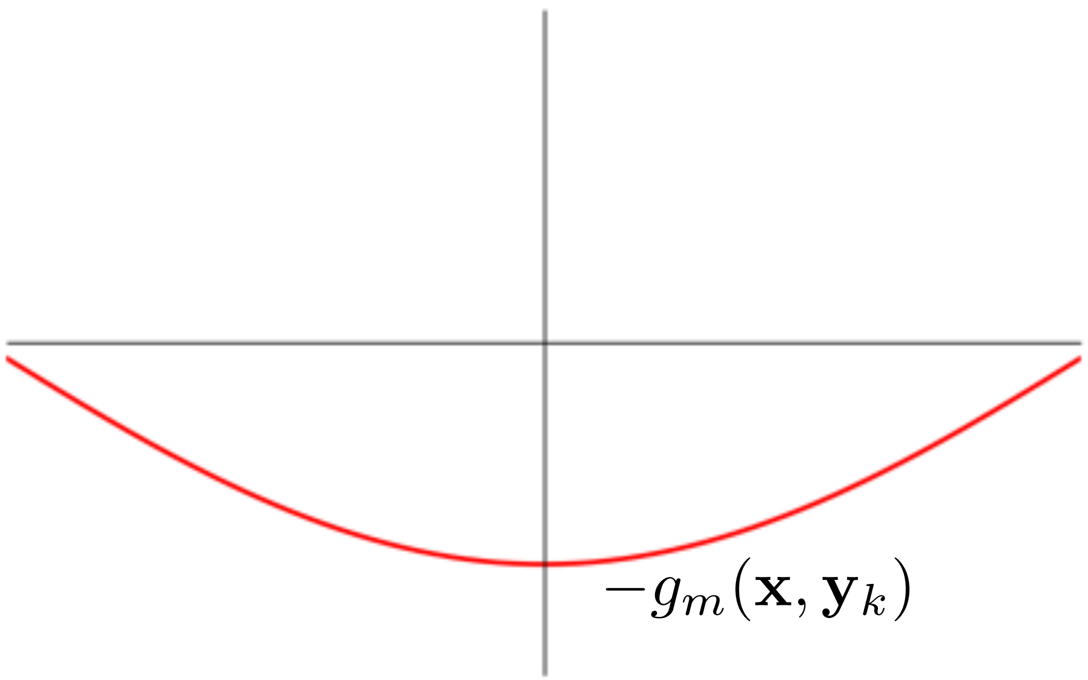
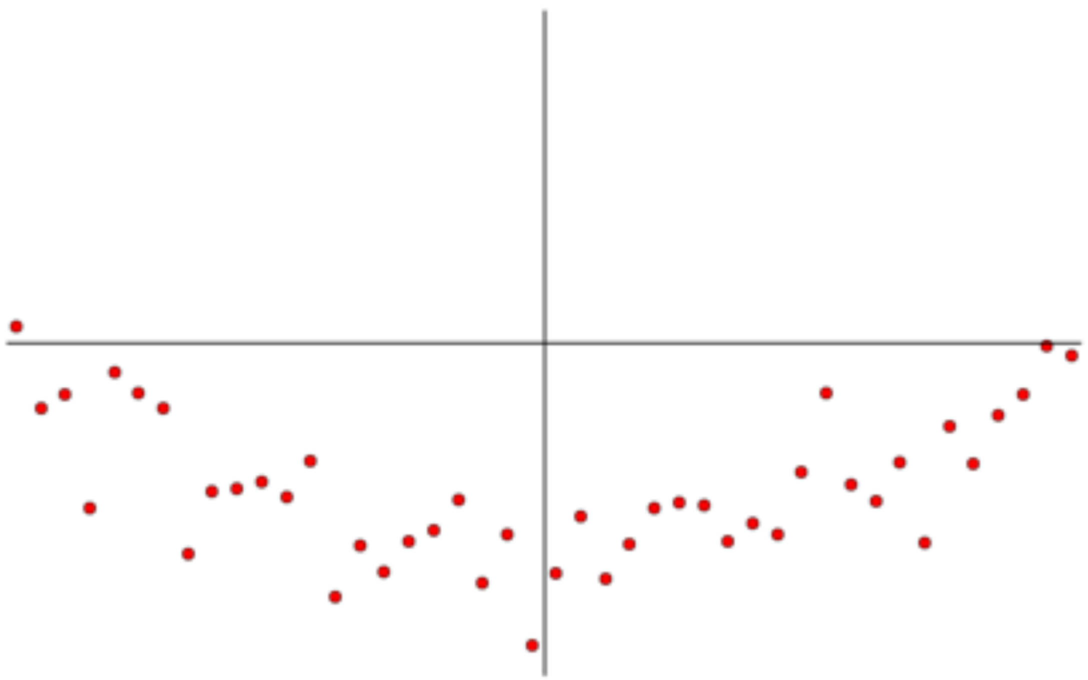


Model Functional Gradients

- Pointwise Functional Gradients



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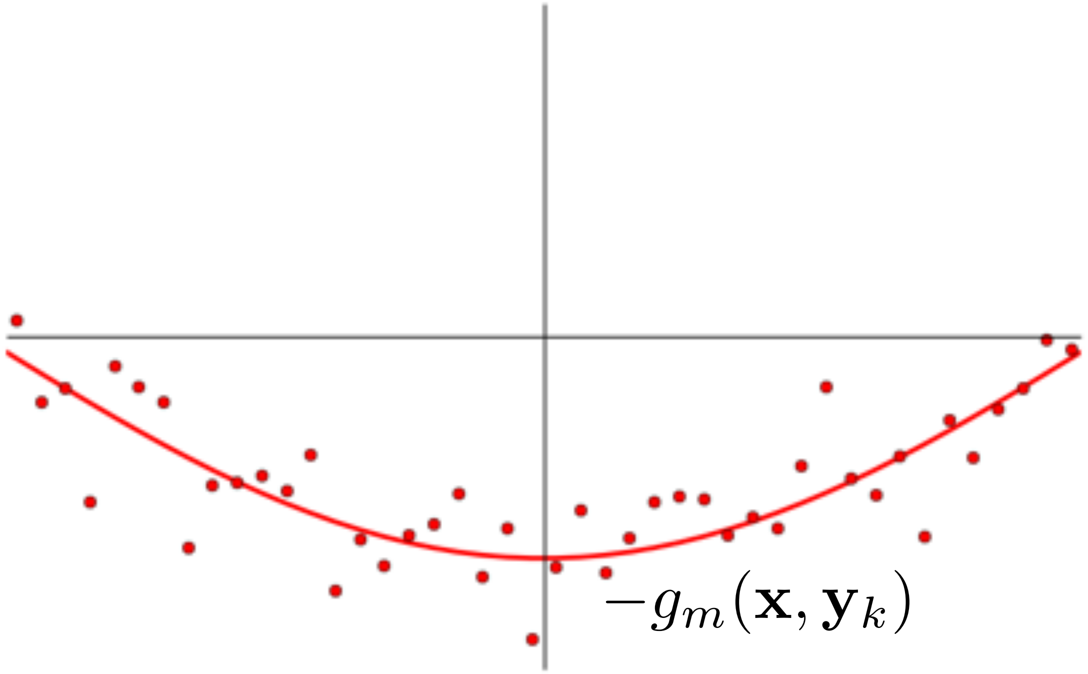

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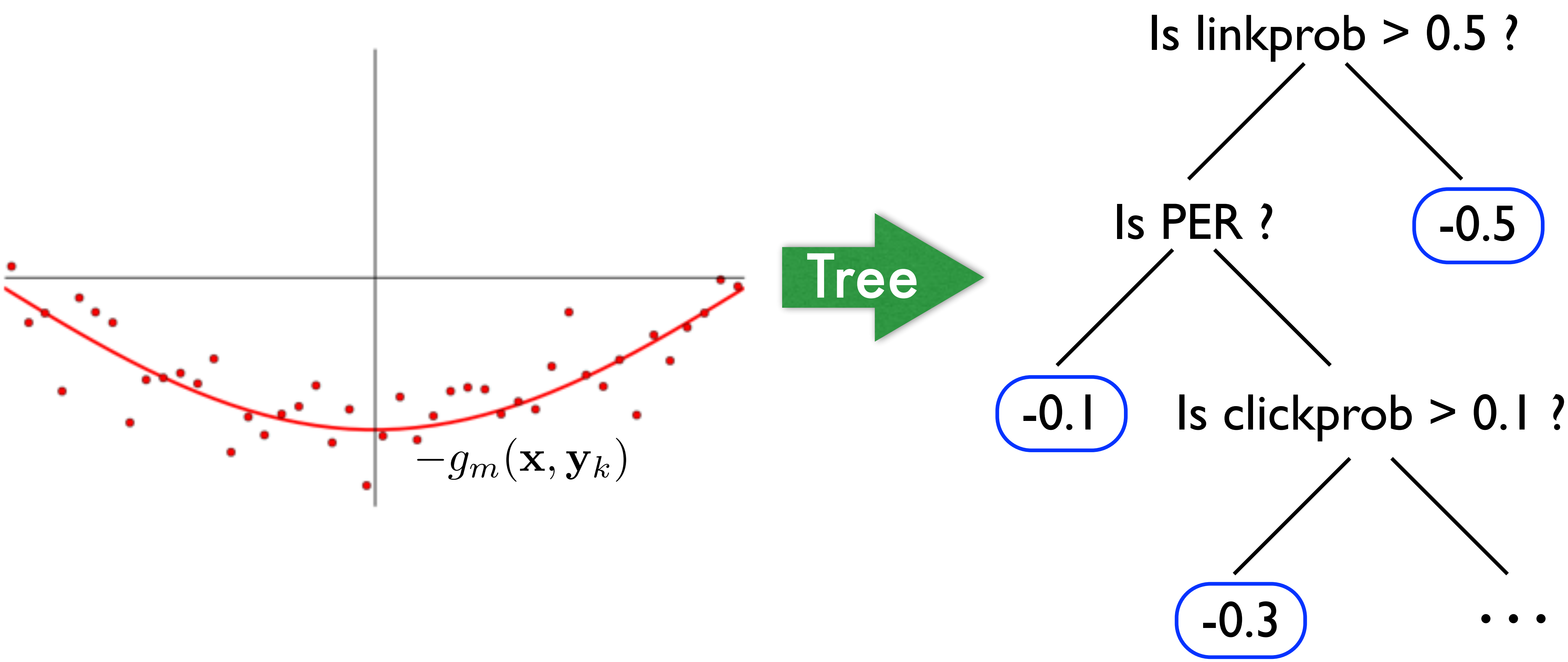

S-MART vs. TreeCRF

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	TreeCRF [Dietterich+, 2004]	S-MART

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Structure	Linear chain	Various structures

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Scoring function	$F^{y_t}(\mathbf{x})$	$F(\mathbf{x}, \mathbf{y}_t)$

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Entity Linking in Short Texts

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- Downstream applications
  - Semantic parsing and question answering [Yih et al., 2015]
  - Relation extraction [Riedel et al., 2013]

Tweet Entity Linking

Yanda @TaylorYanda · 33s
Eli Manning and the **New York Giants** are going to win the World Series
#Game7

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- Powerful statistic dense features [Guo et al., 2013]
  - The probability of a surface form to be an entity
  - View count of a Wikipedia page
  - Textual similarity between a tweet and a Wikipedia page

System Overview

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  - Choose top 20 entity candidates for each surface form
  - Add a special NIL entity to represent no entity should be fired here

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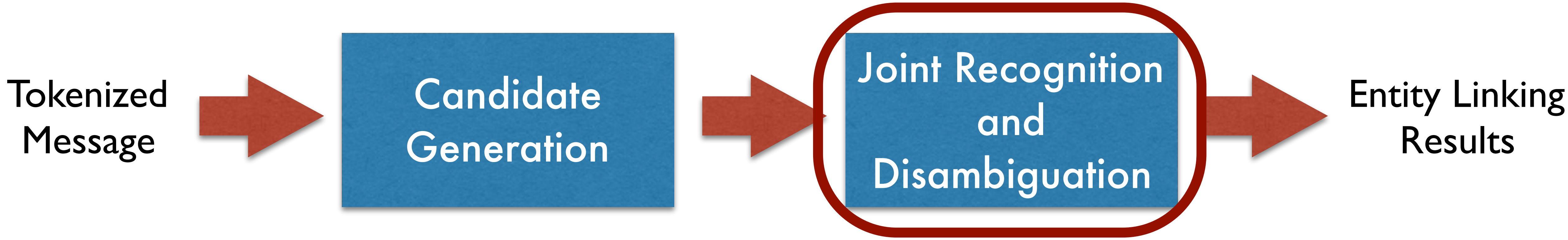

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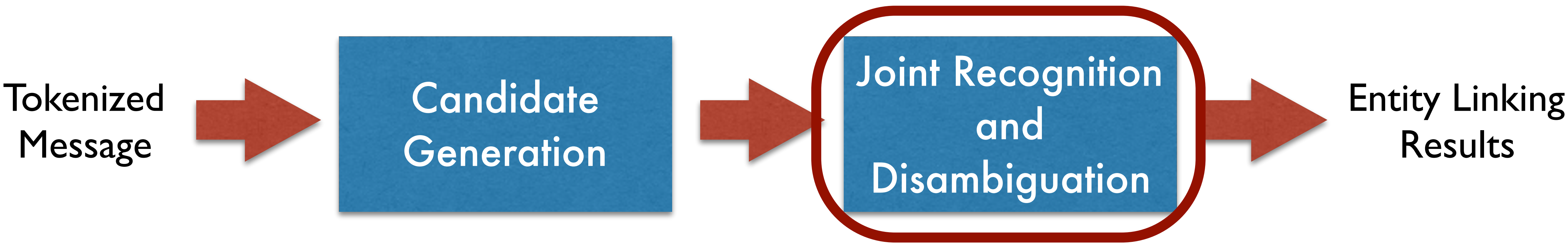

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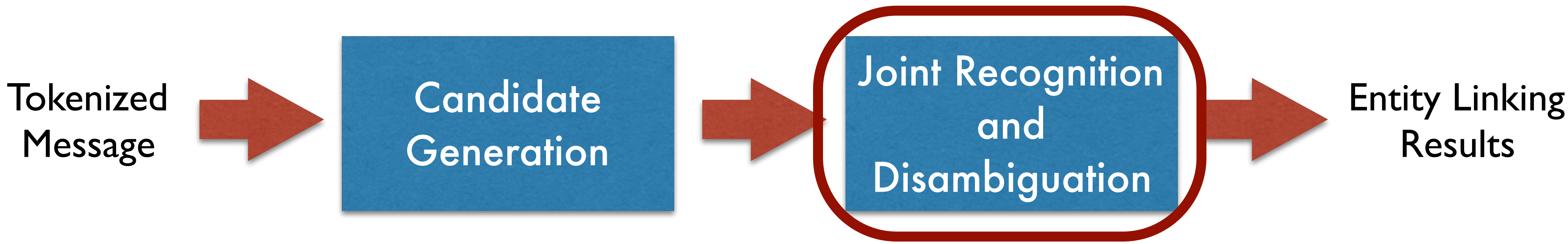

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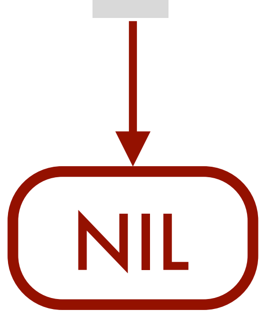

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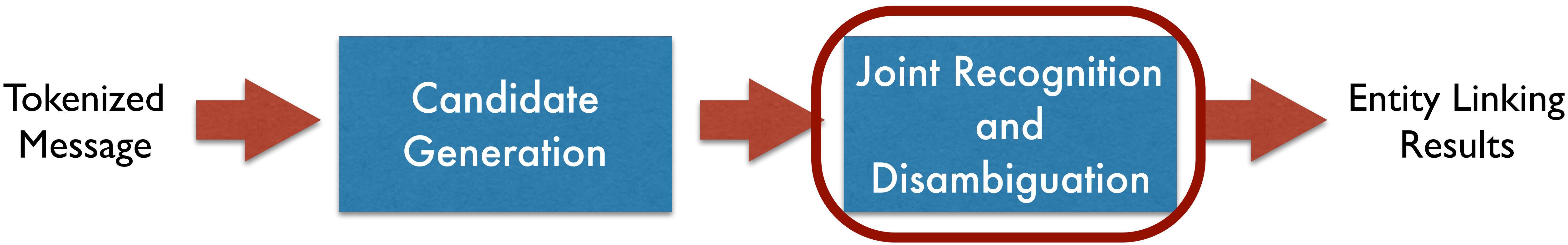

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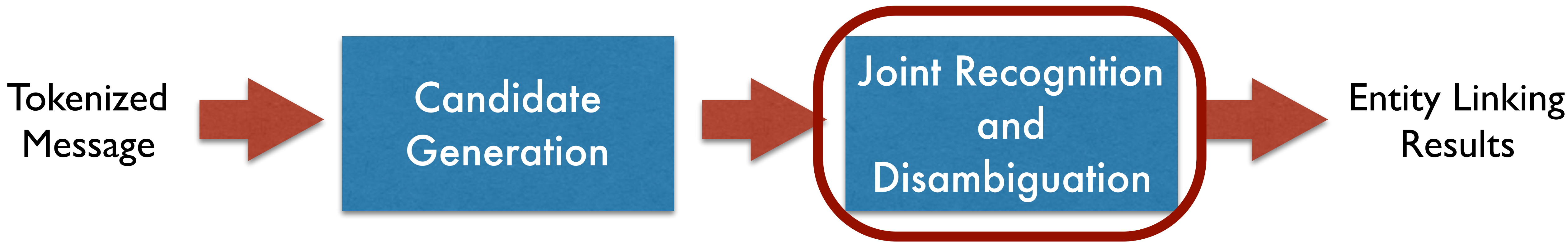

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Eli_Manning

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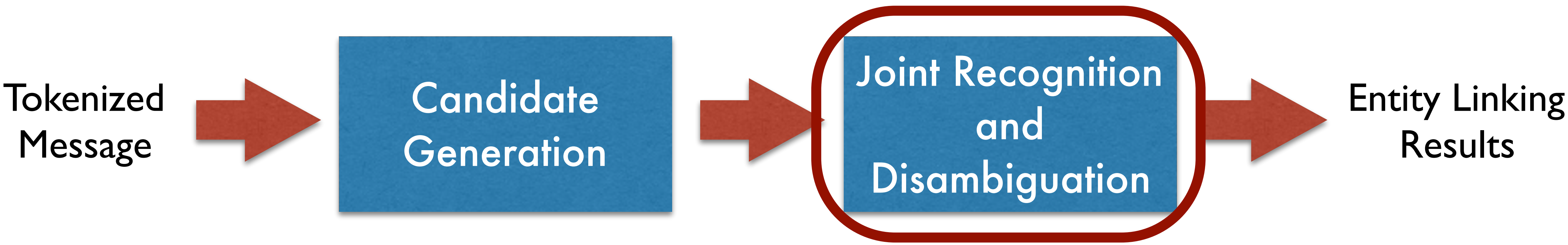

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S-MART for Tweet Entity Linking

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- Logistic loss

$$\begin{aligned} L(\mathbf{y}^*, S(\mathbf{x}, \mathbf{y})) &= -\log P(\mathbf{y}^*|\mathbf{x}) \\ &= \log Z(\mathbf{x}) - S(\mathbf{x}, \mathbf{y}^*) \end{aligned}$$

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$$g_{ku} = \frac{\partial L}{\partial F(\mathbf{x}, y_k = u_k)}$$
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Non-overlapping Inference

Inference: Forward Algorithm

Eli Manning and the New York Giants are going to win the World Series

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Eli Manning and the New York Giants are going to win the World Series

Eli	*New*	*win*	*World*
Eli Manning	*New York*		*World Series*
Manning	*York*		*Series*
	New York Giants		
	Giants		

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$$\alpha(u_k, k) = \boxed{\exp(F(\mathbf{x}, y_k = u_k))} \cdot \prod_{p=1}^{P-1} \exp(F(\mathbf{x}, y_{k-p} = \mathbf{Nil})) \cdot \sum_{u_{k-P}} \alpha(u_{k-P}, k-P)$$

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$$\beta(u_k, k) = \sum_{u_{k+Q}} \exp(F(\mathbf{x}, y_{k+Q} = u_{k+Q}))$$

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Data

- Named Entity Extraction & Linking (NEEL) Challenge datasets [Cano et al., 2014]
- TACL datasets [Fang & Chang, 2014]

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Data	#Tweet	#Entity	Date
NEEL Train	2,340	2,202	Jul. ~ Aug. 11
NEEL Test	1,164	687	Jul. ~ Aug. 11
TACL-IE	500	300	Dec. 12
TACL-IR	980	-	Dec. 12

Evaluation Methodology

- IE-driven Evaluation [Guo et al., 2013]
  - Standard evaluation of the system ability on extracting entities from tweets
  - Metric: macro F-score

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- IR-driven Evaluation [Fang & Chang, 2014]
  - Evaluation of the system ability on disambiguation of the target entities in tweets
  - Metric: macro F-score on query entities

Algorithms

	Structured	Non-linear	Tree-based
Structured Perceptron	✓		
Linear SSVM*	✓		
Polynomial SSVM	✓	✓	
LambdaRank		✓	
MART#		✓	✓
S-MART	✓	✓	✓

* previous state of the art system

winning system of NEEL challenge 2014

IE-driven Evaluation

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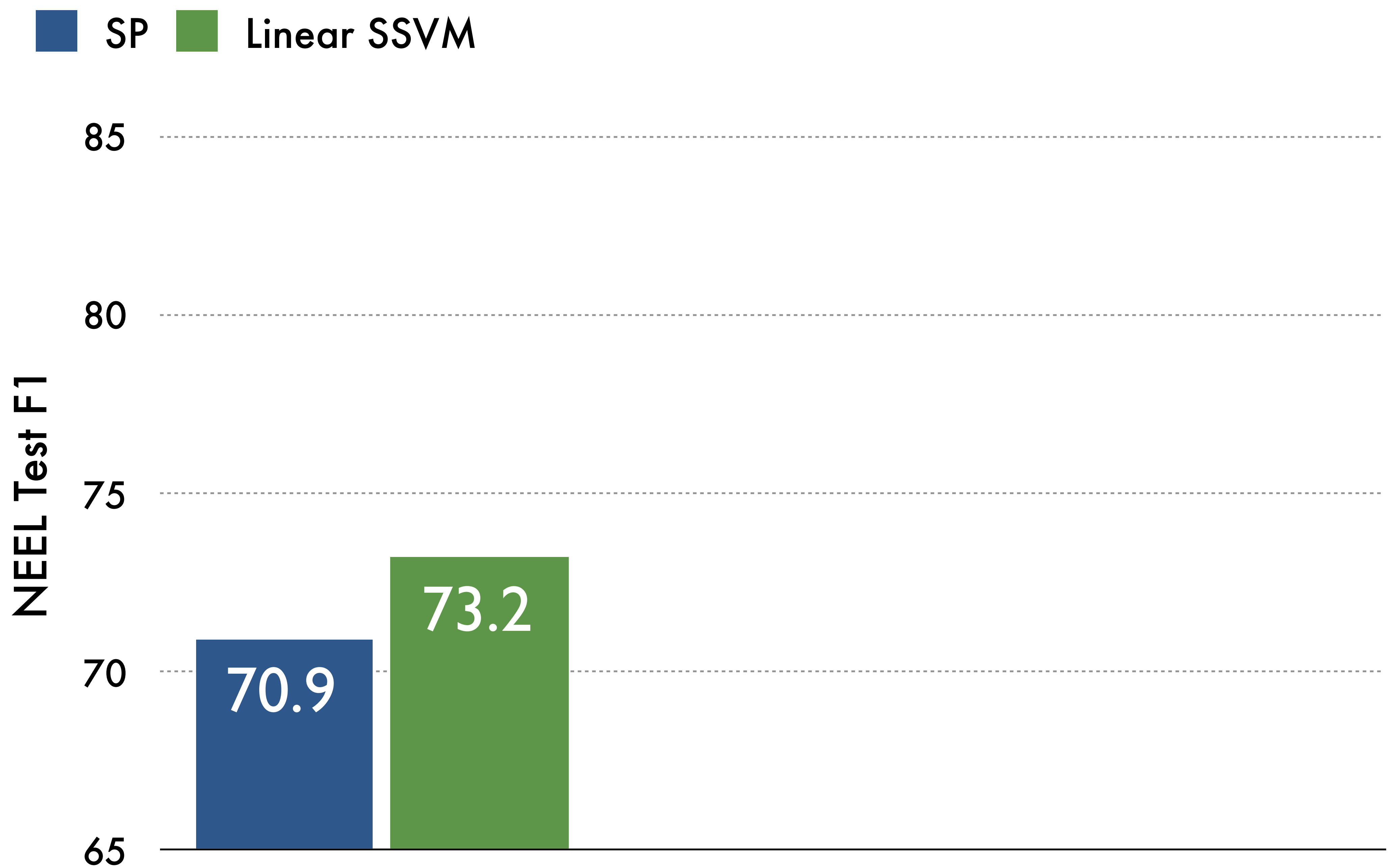

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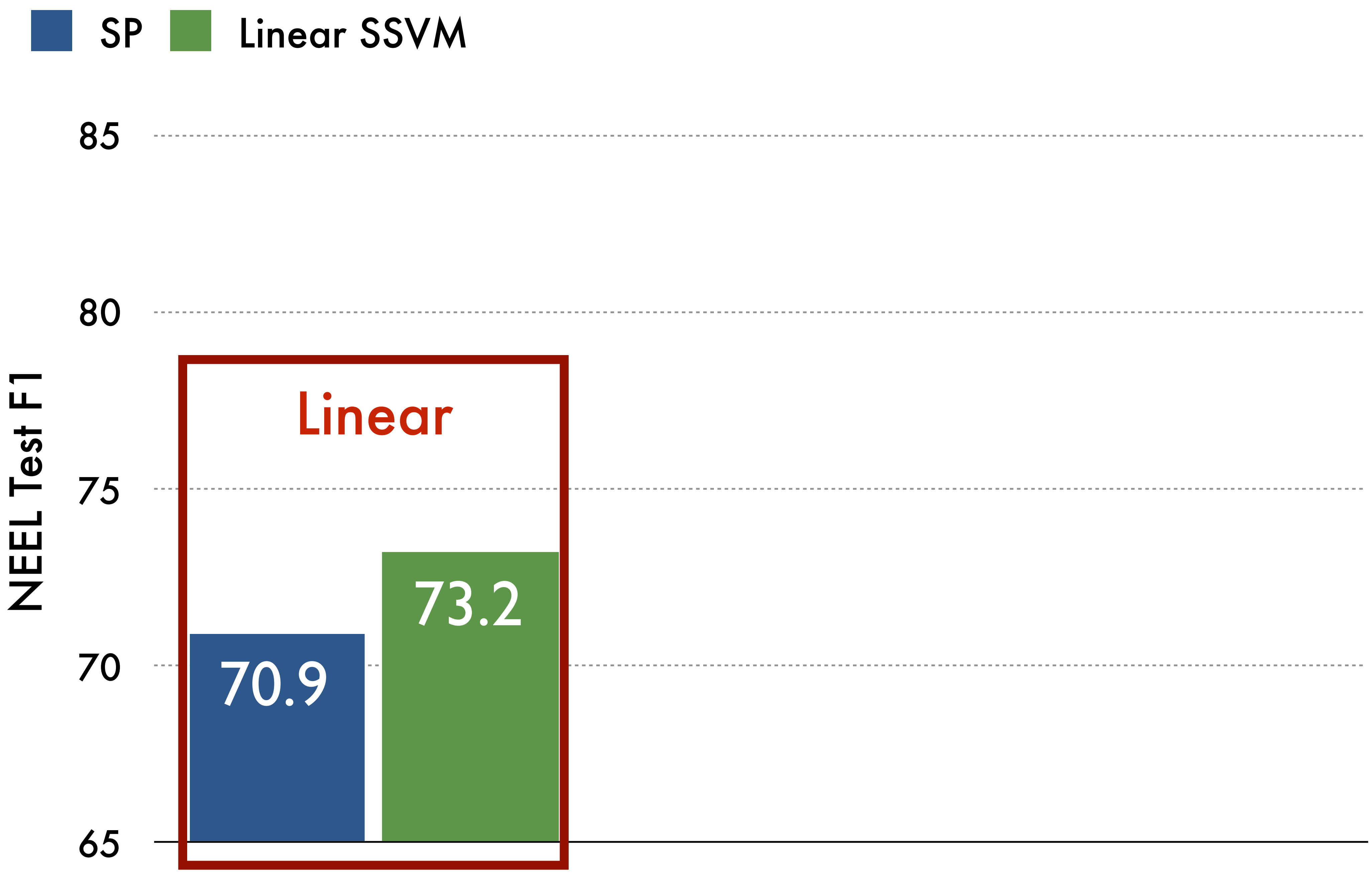

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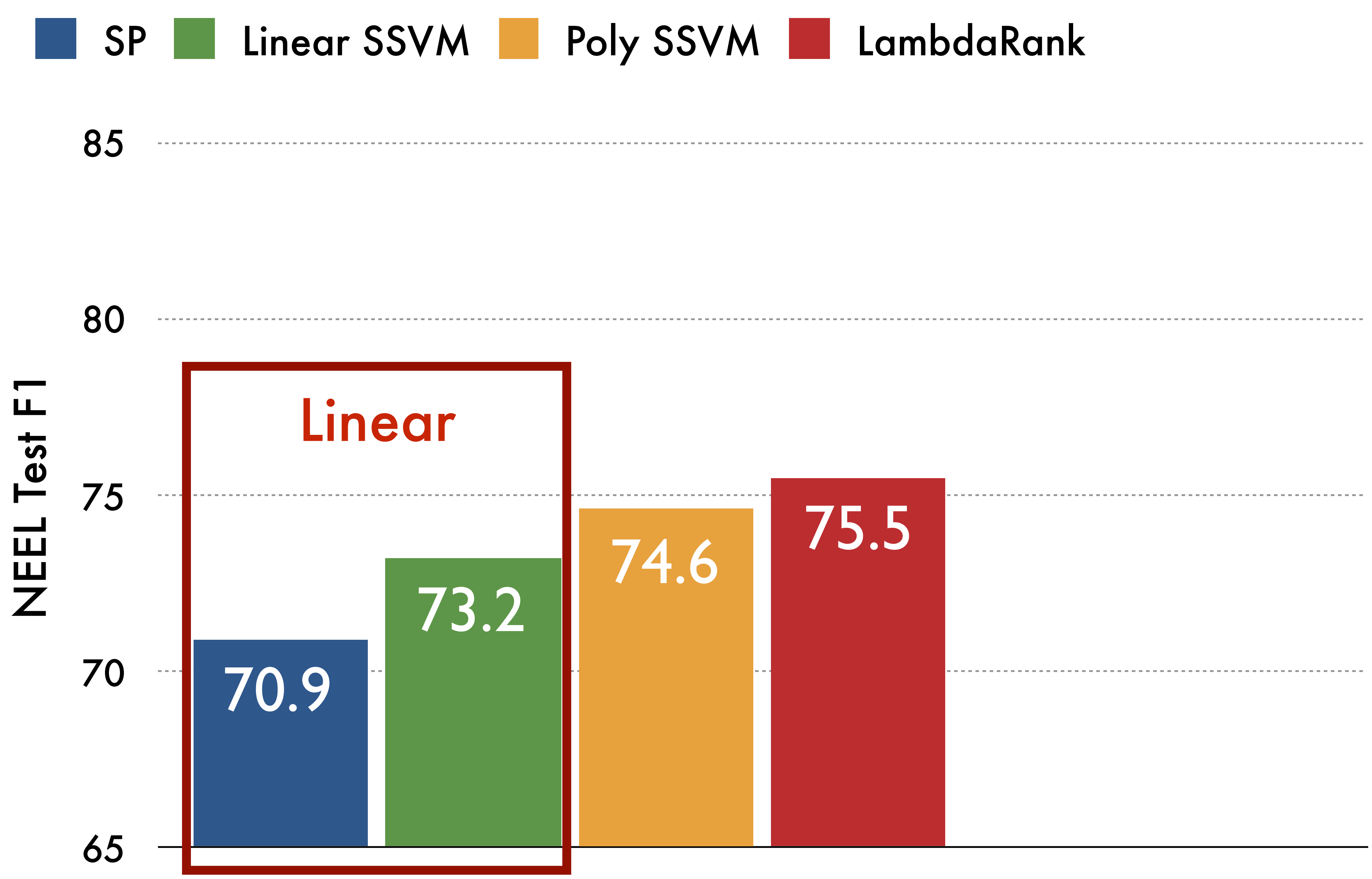

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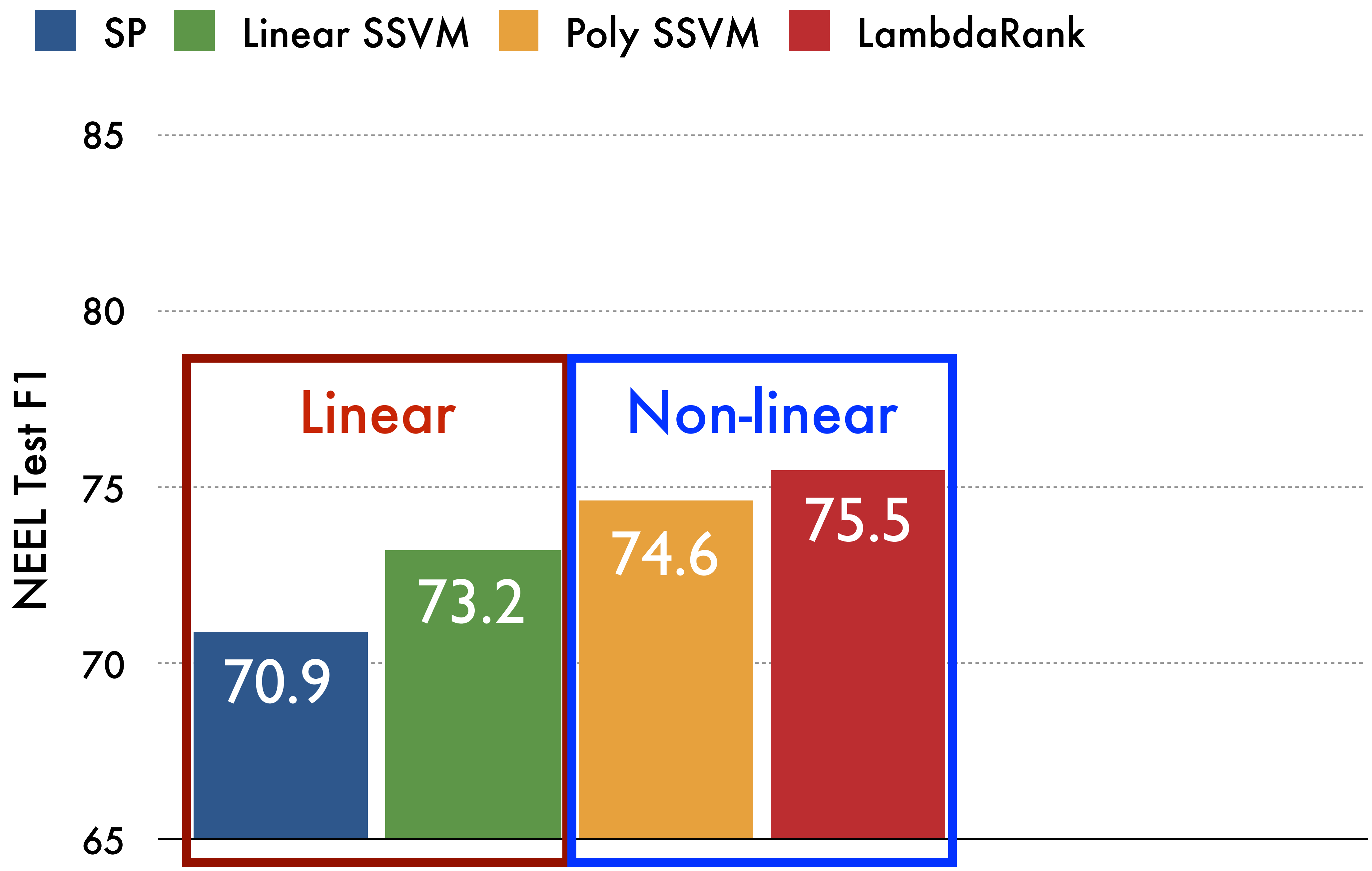

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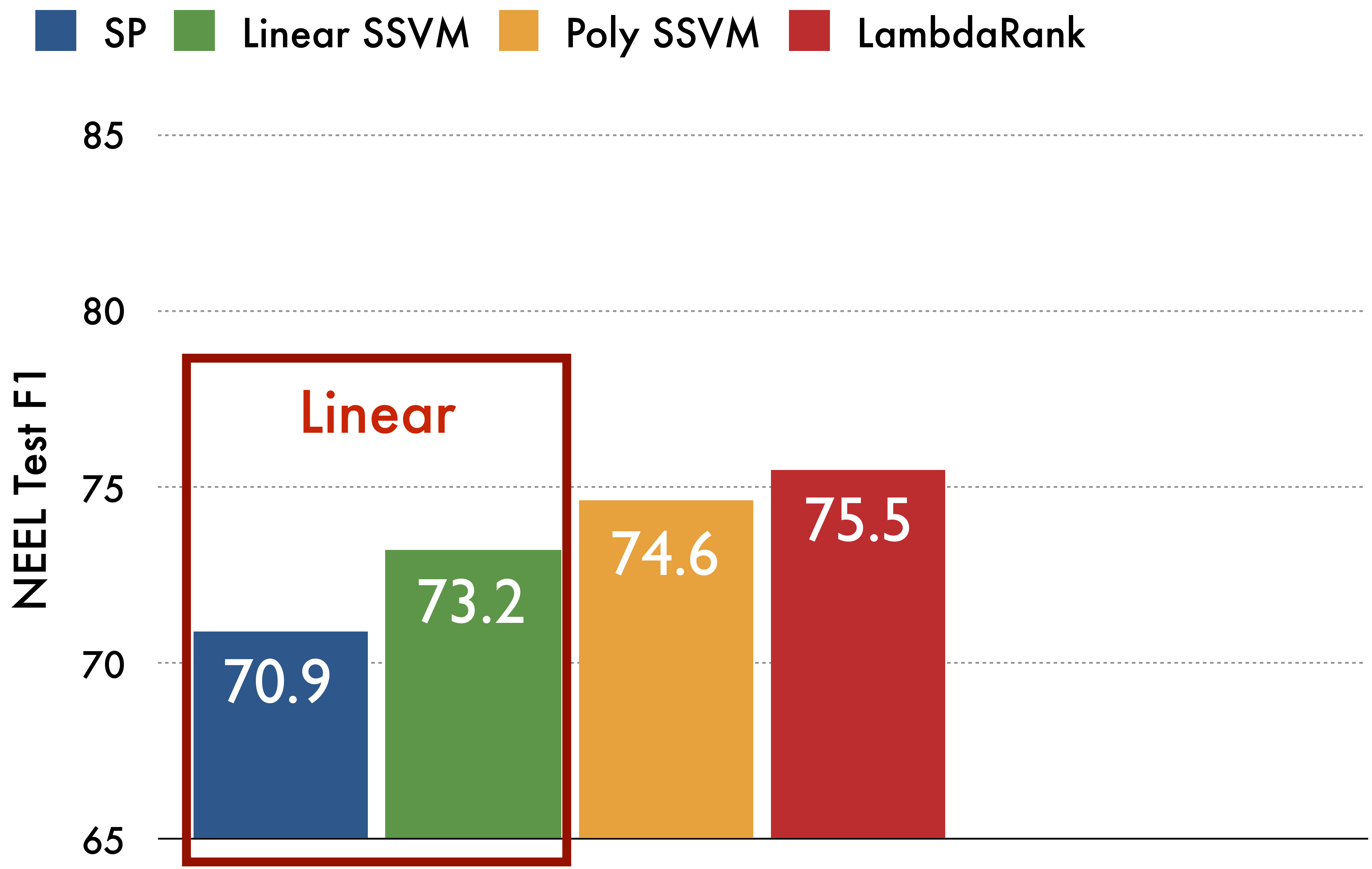

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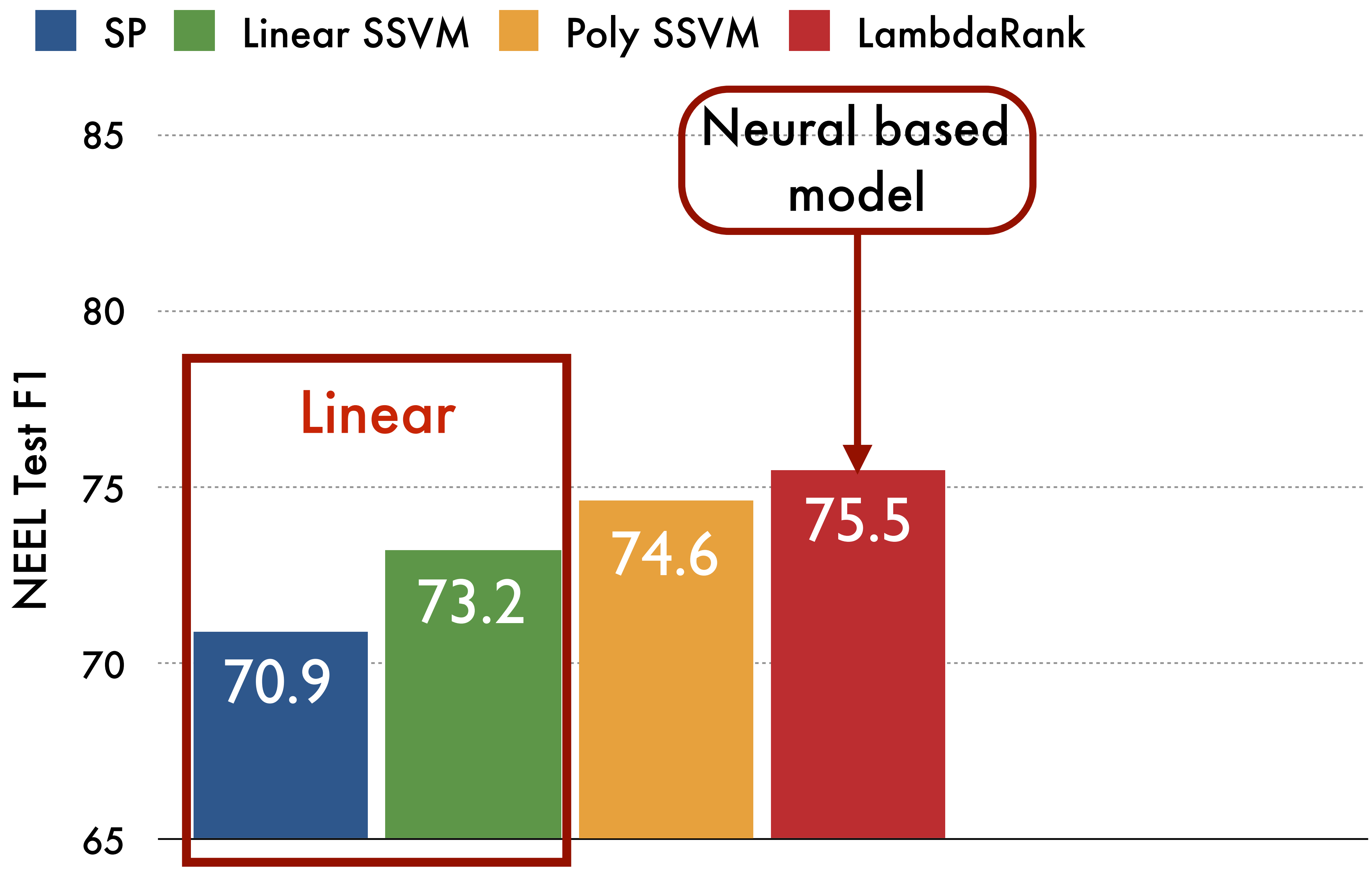

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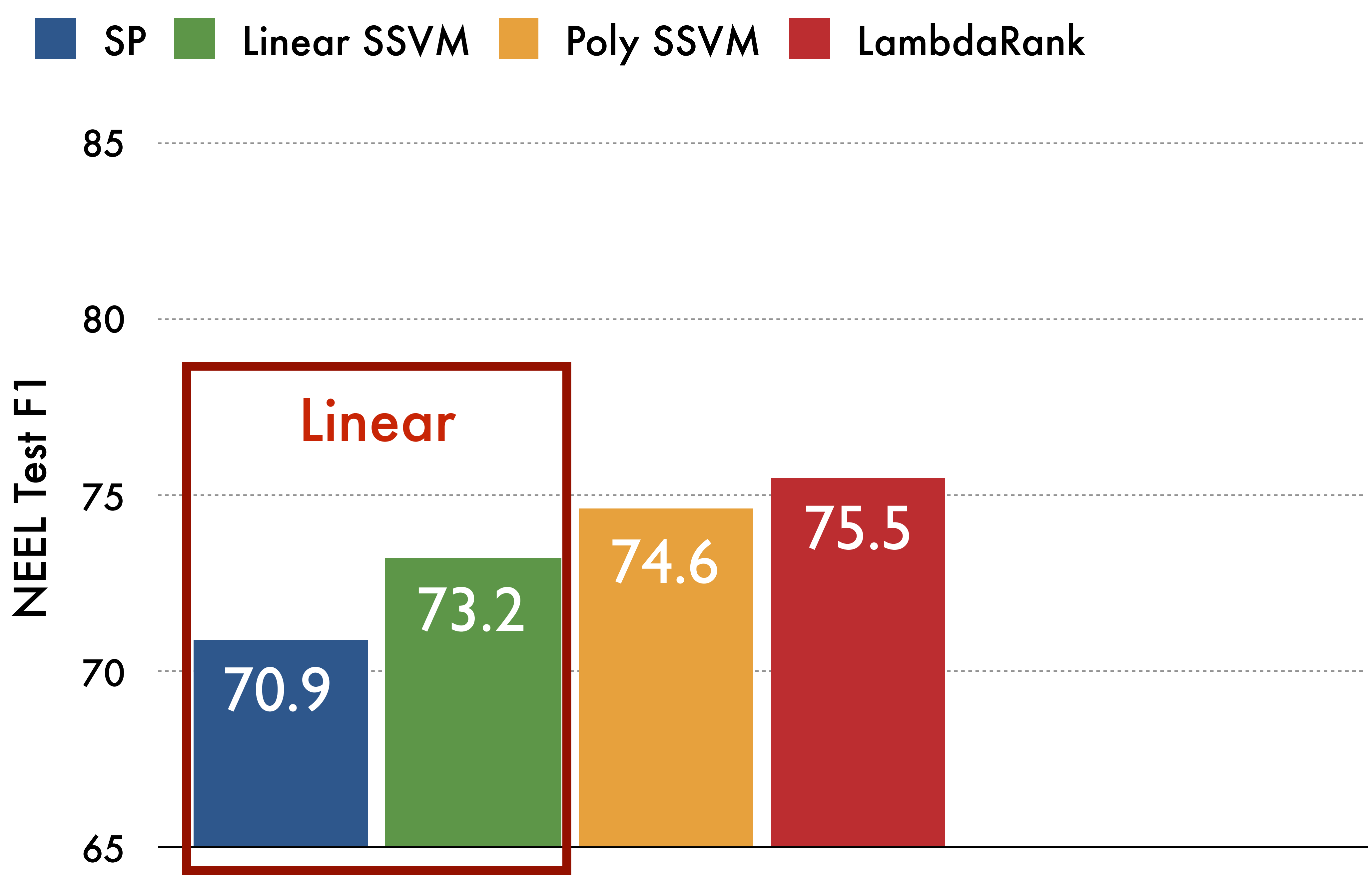

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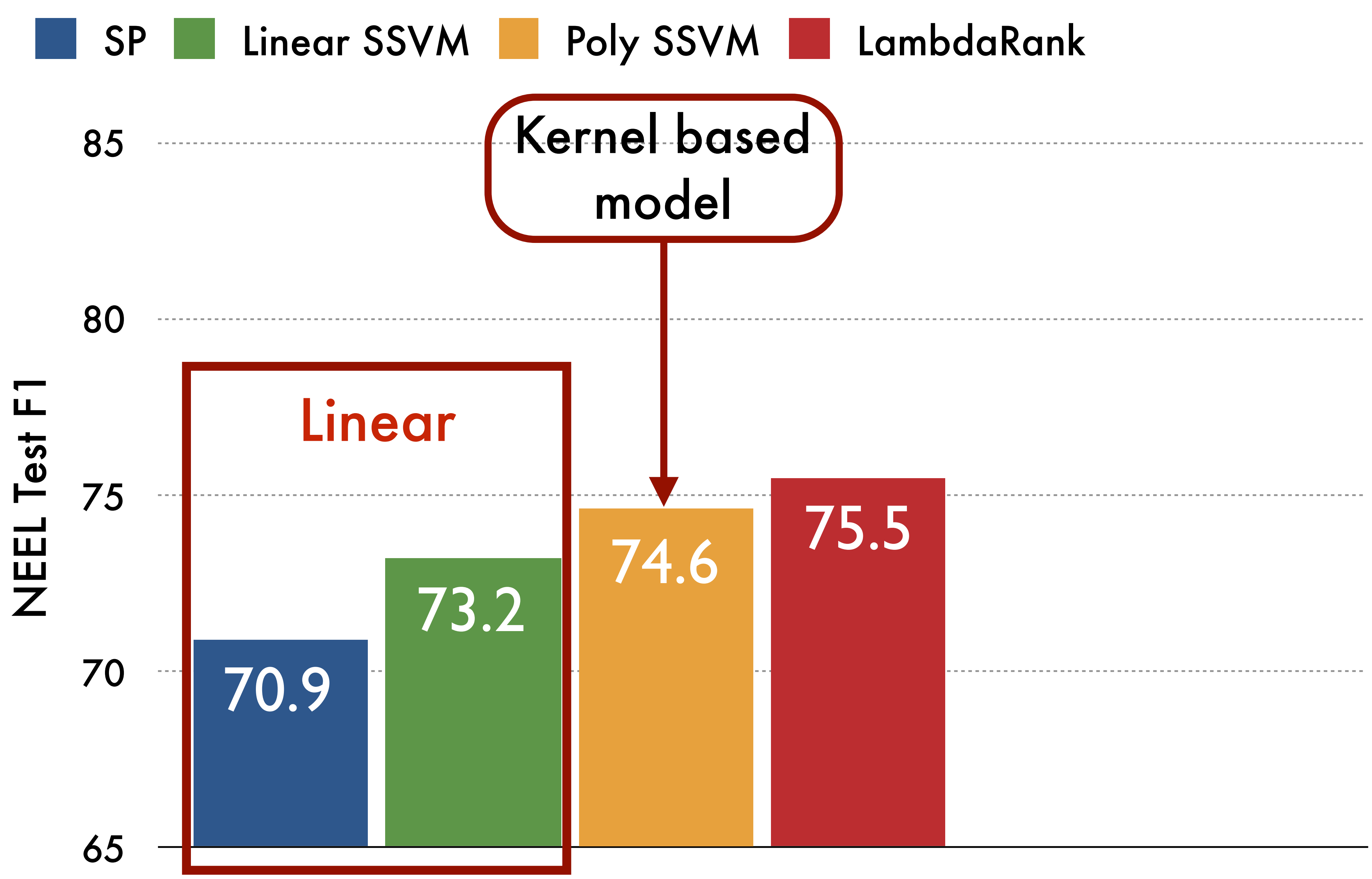

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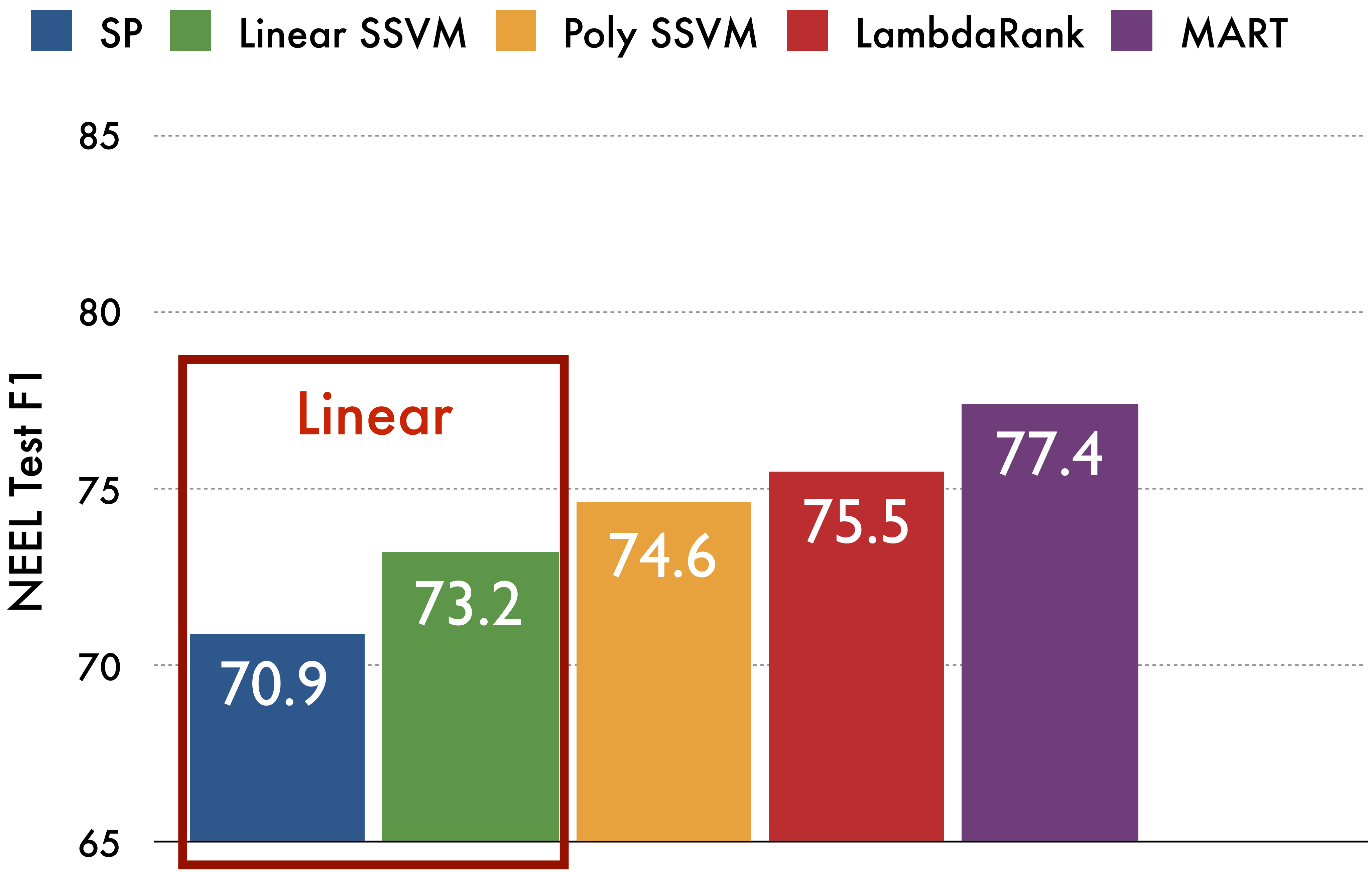

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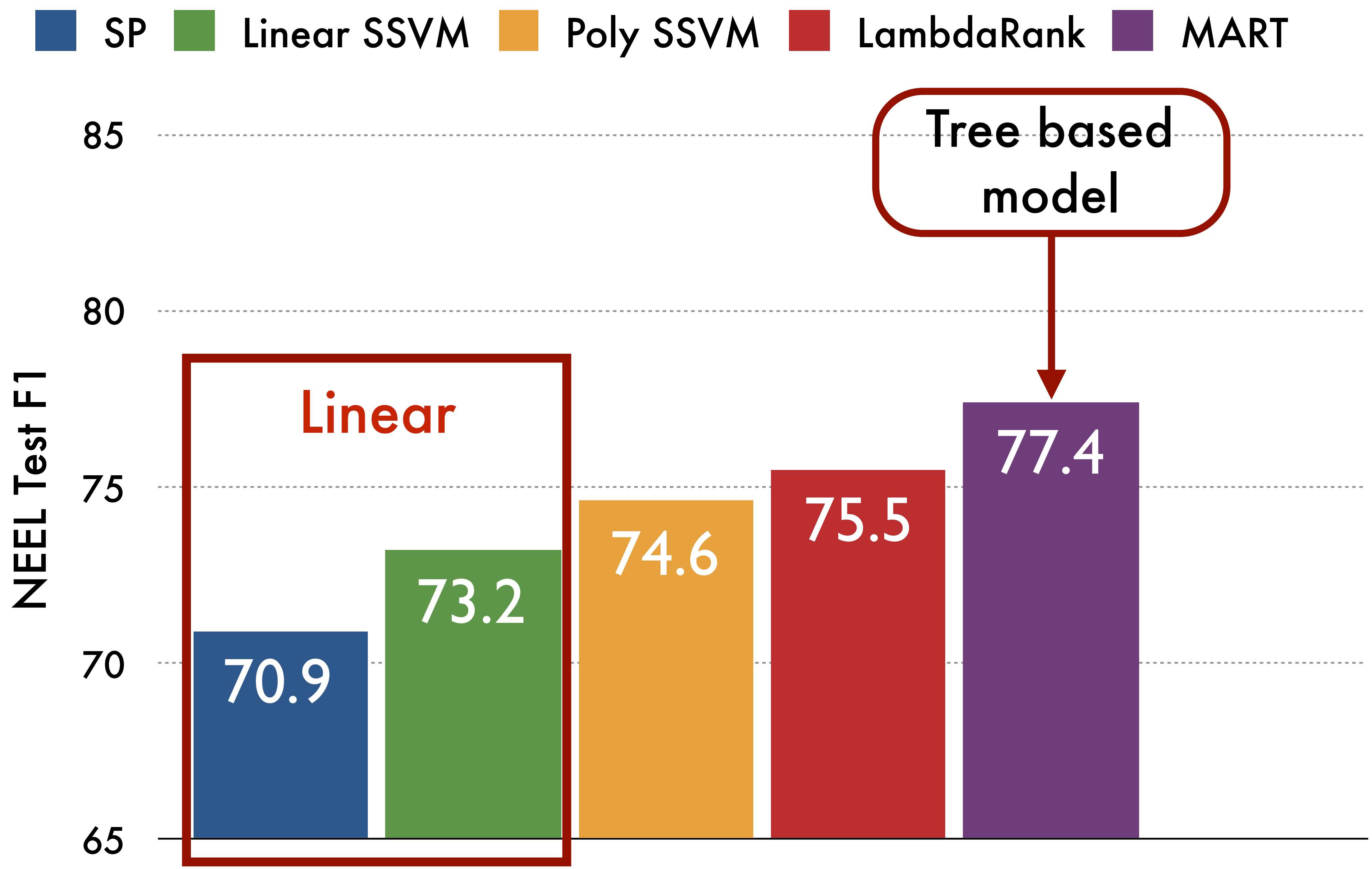

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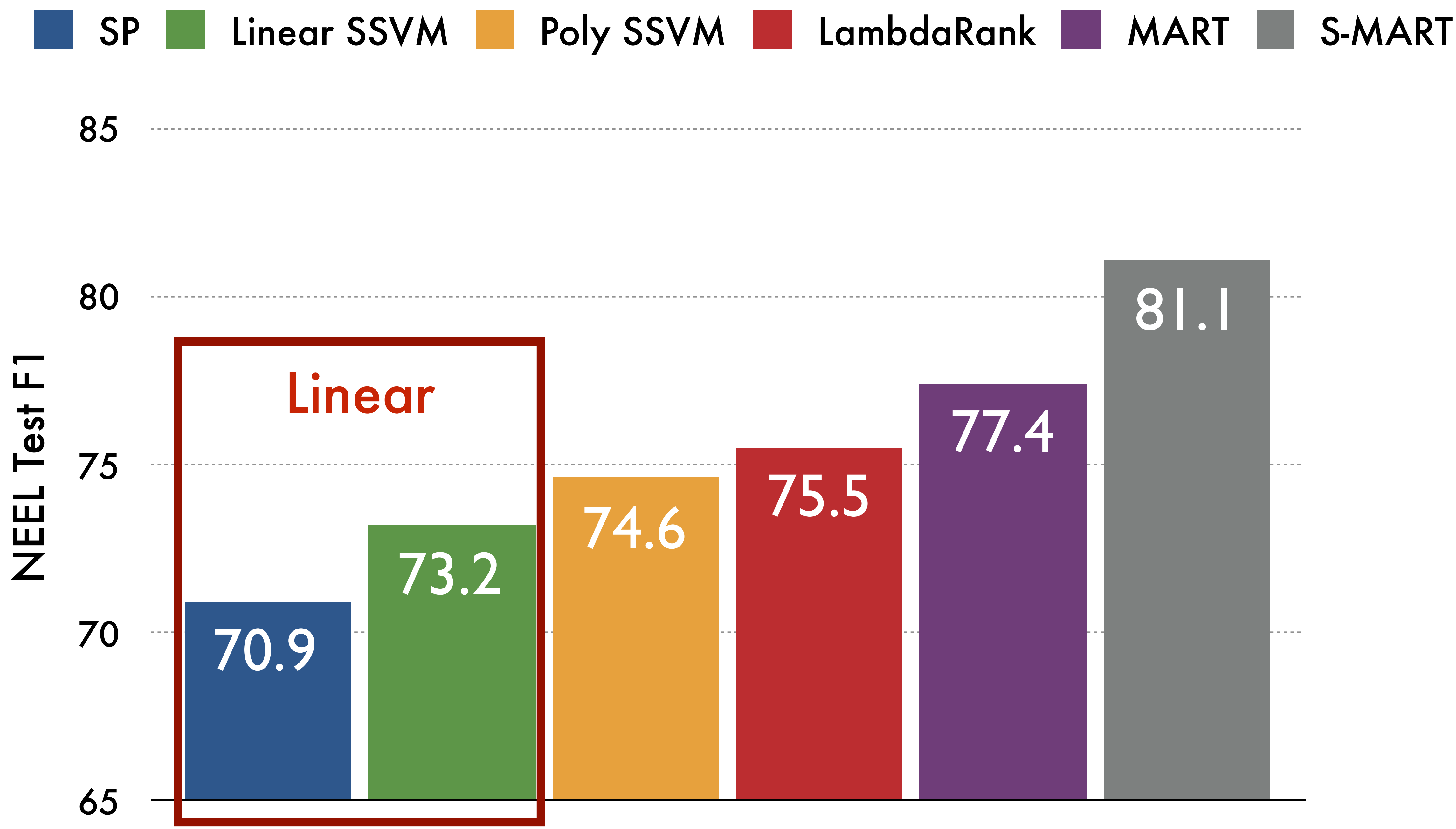

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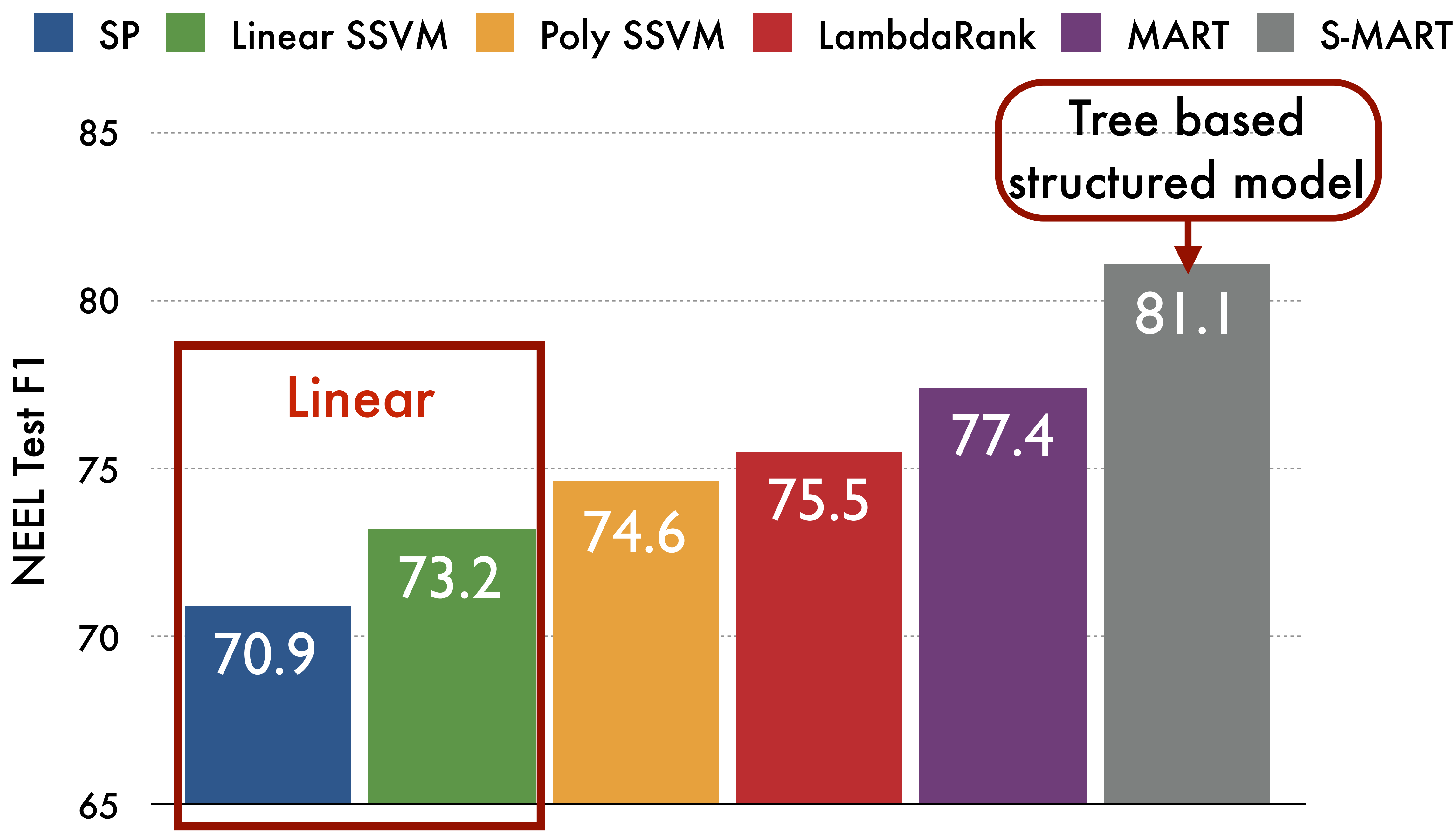

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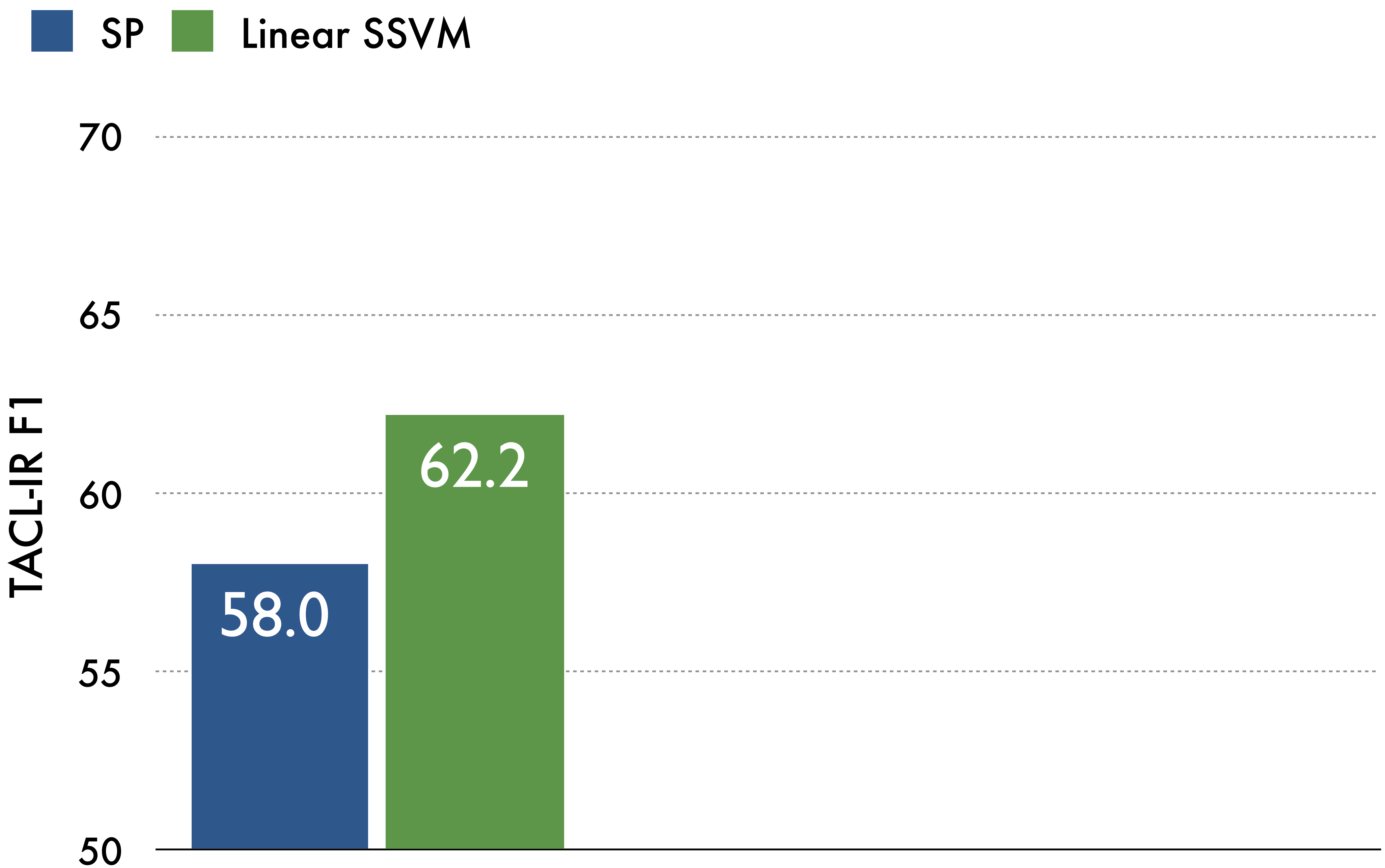

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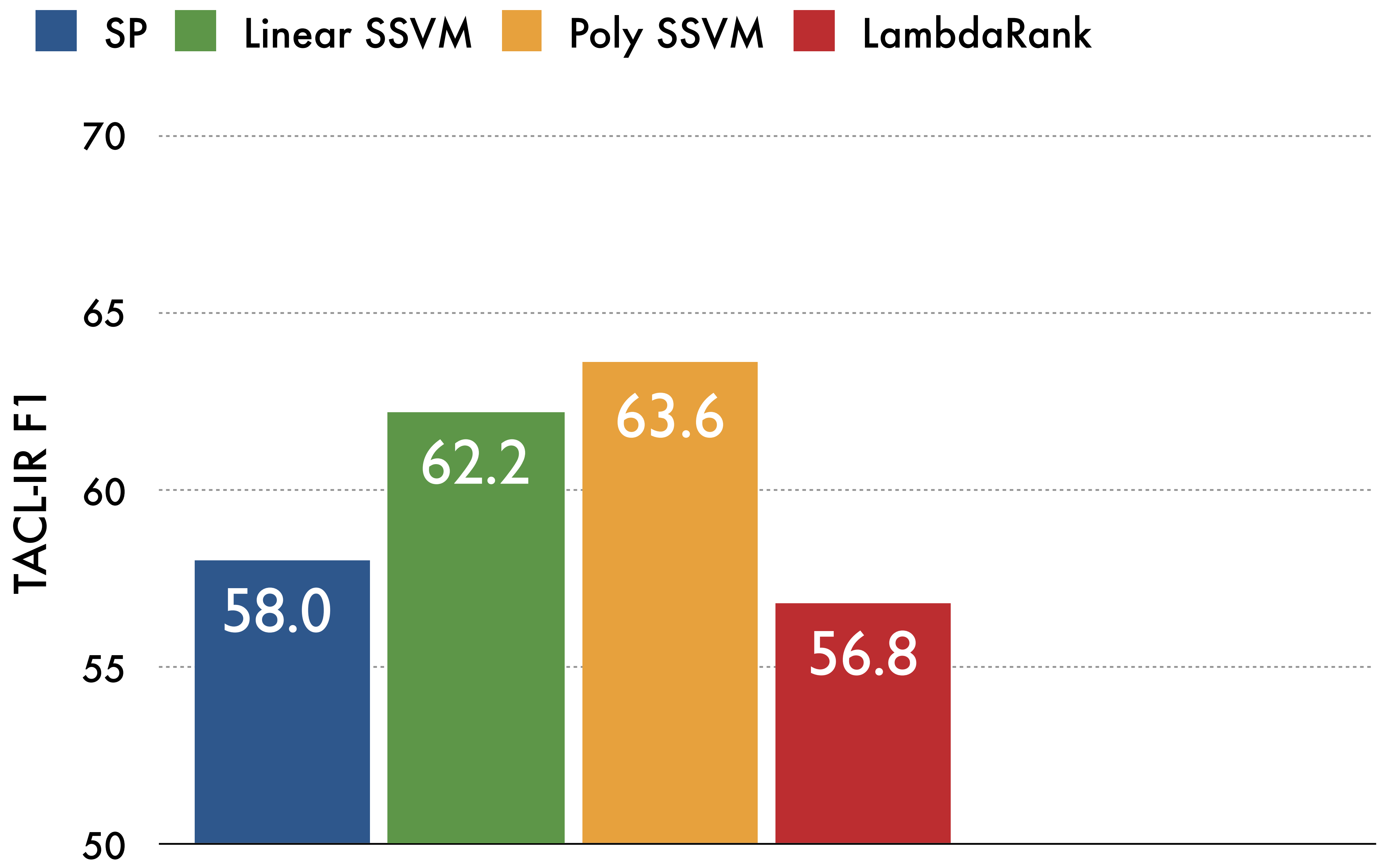

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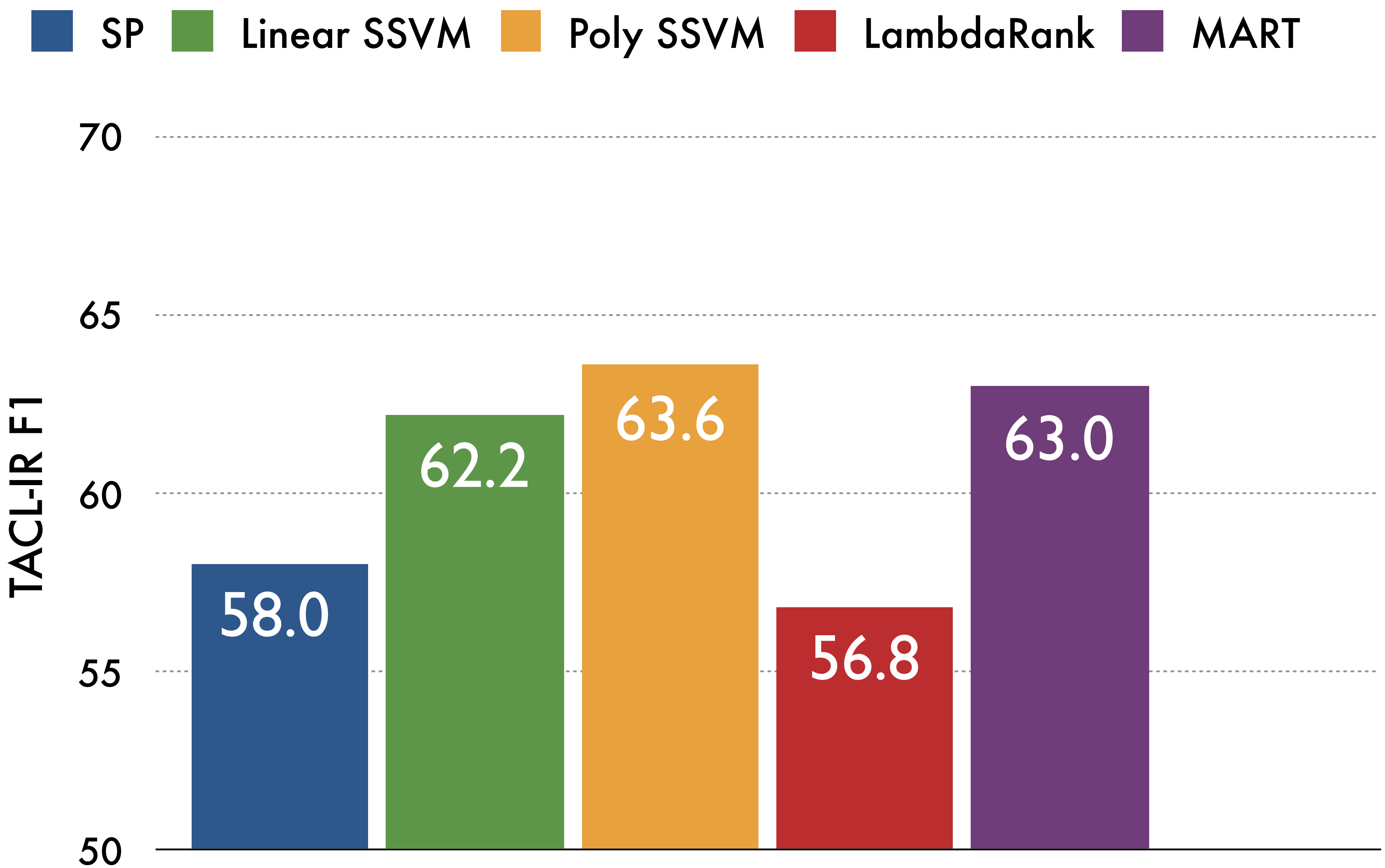

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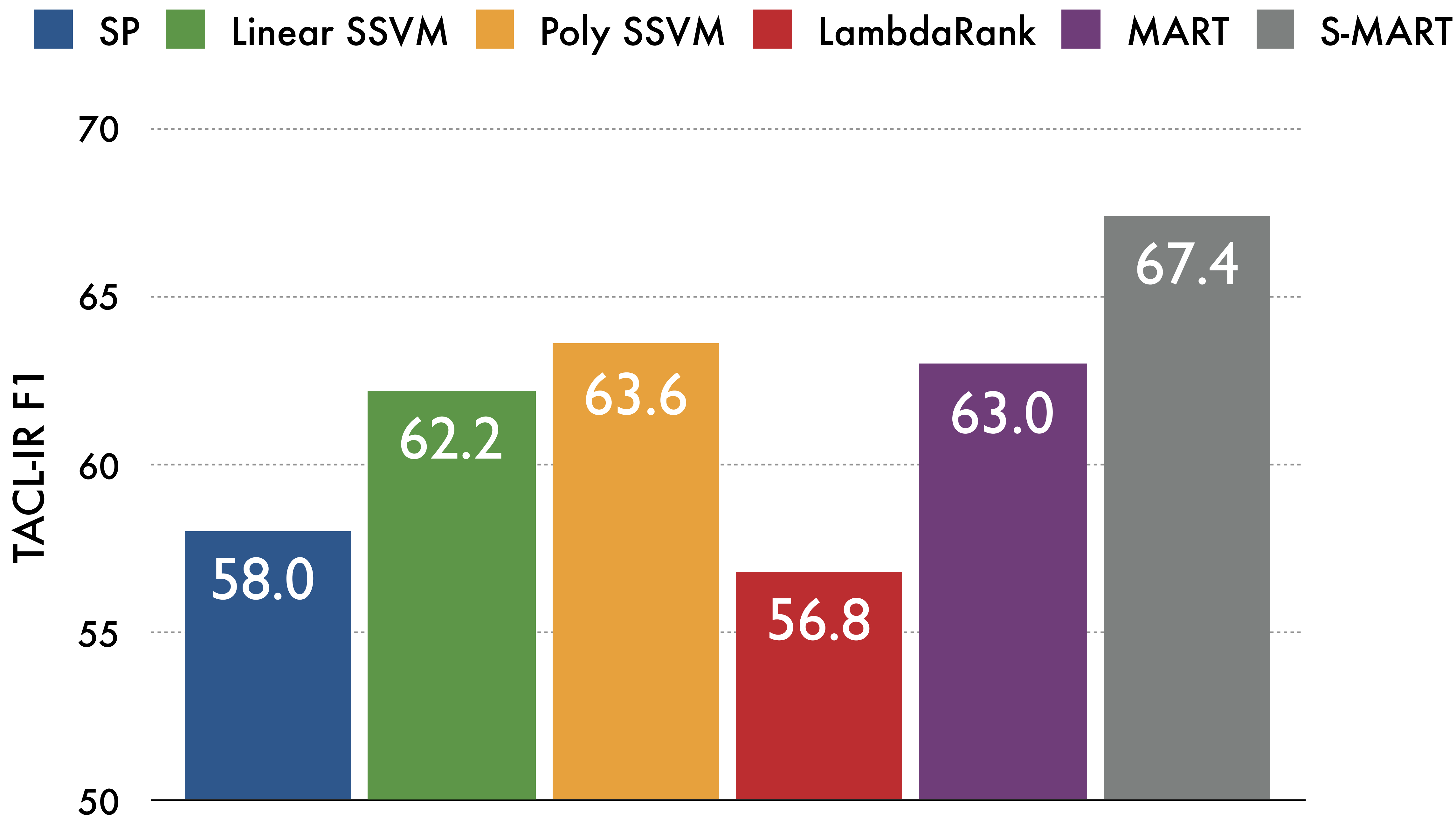

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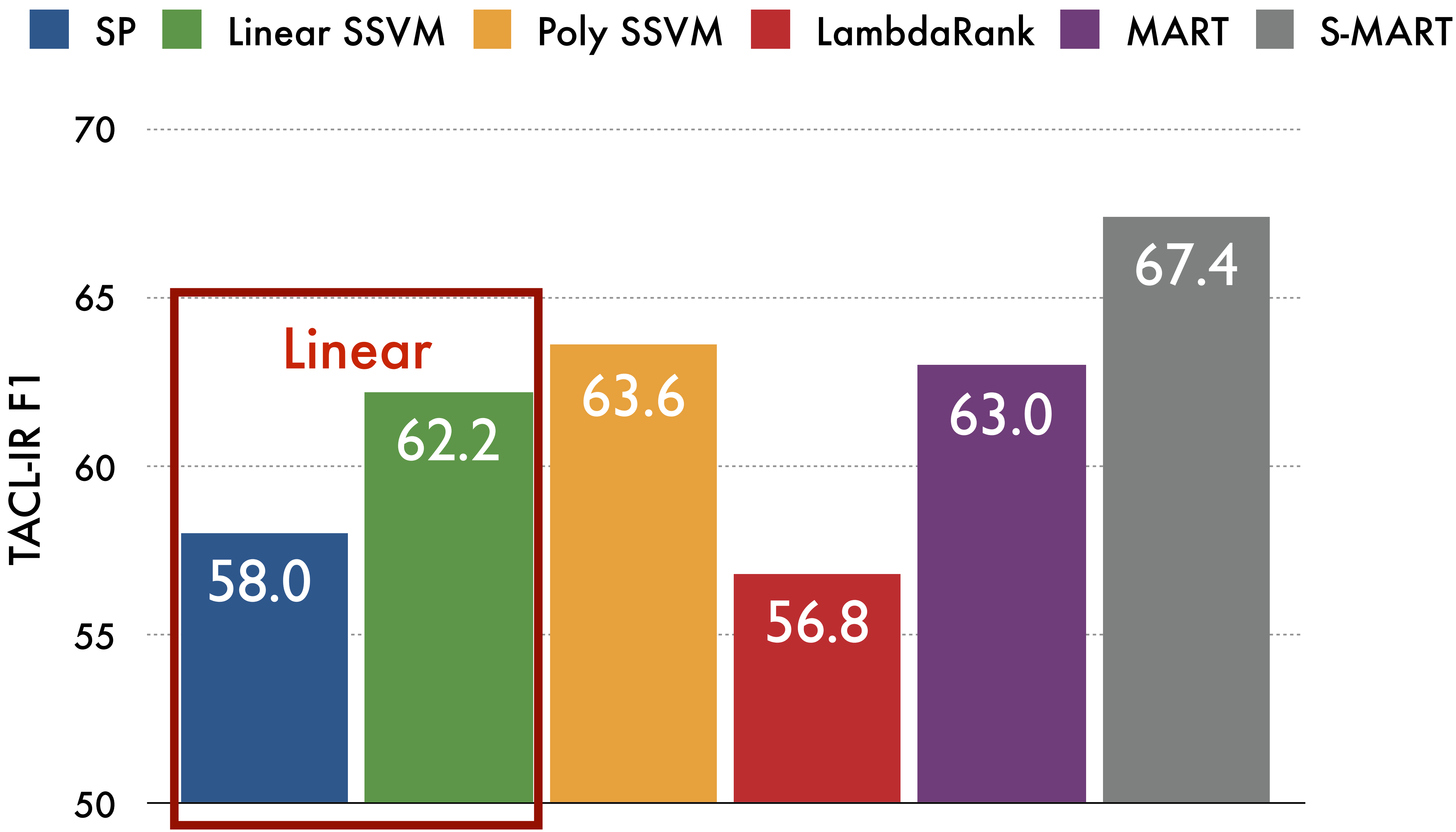

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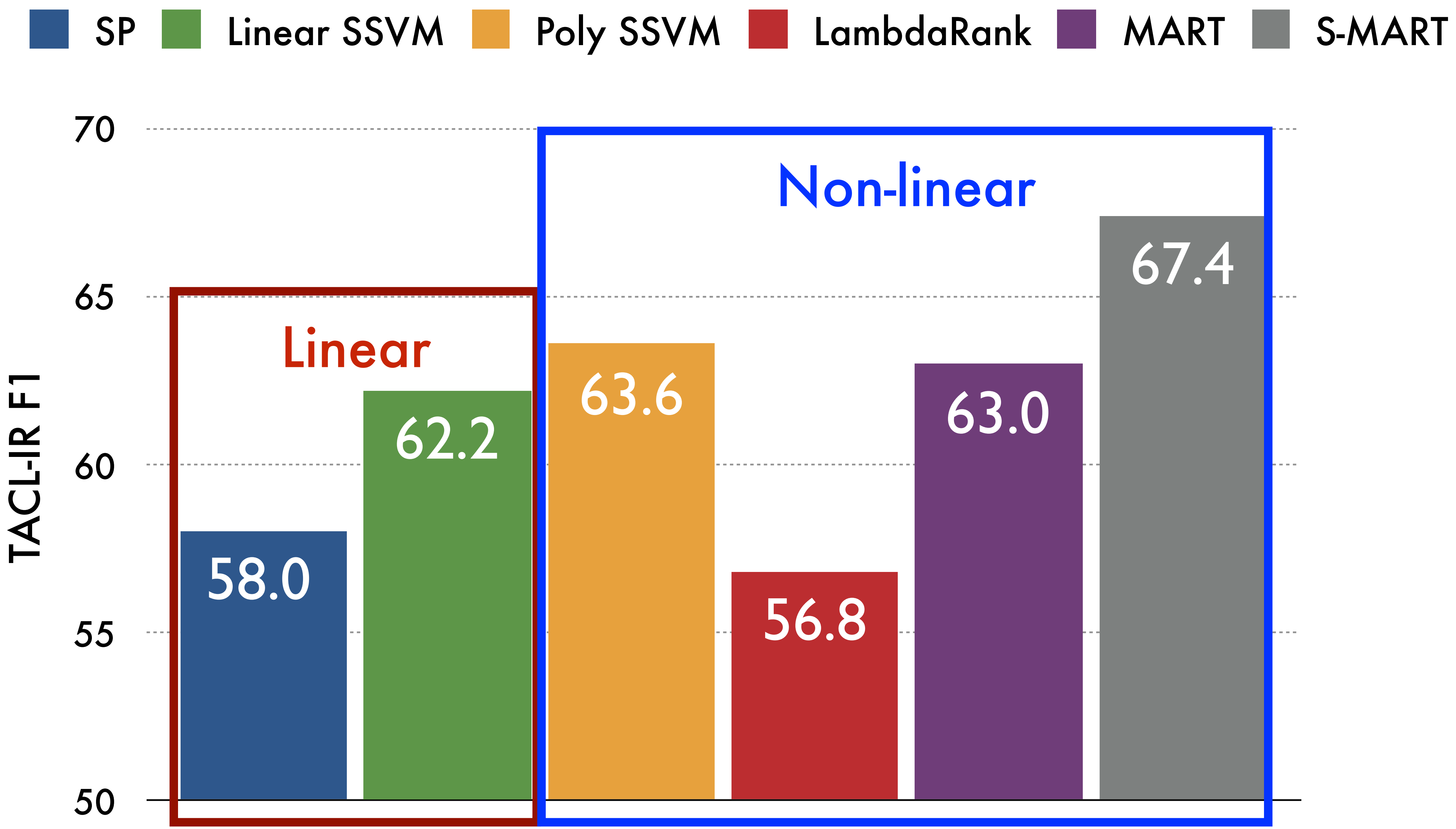

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  - Generalization of TreeCRF
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- Application: Knowledge base QA (outstanding paper of ACL'15)
  - Our system is a core component of the QA system.
- Rise of non-linear models
  - We can try advanced neural based structured algorithms
  - It's worth to try different non-linear models

Thank you!