Towards Hardware-Aware Sentiment Analysis

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Outline

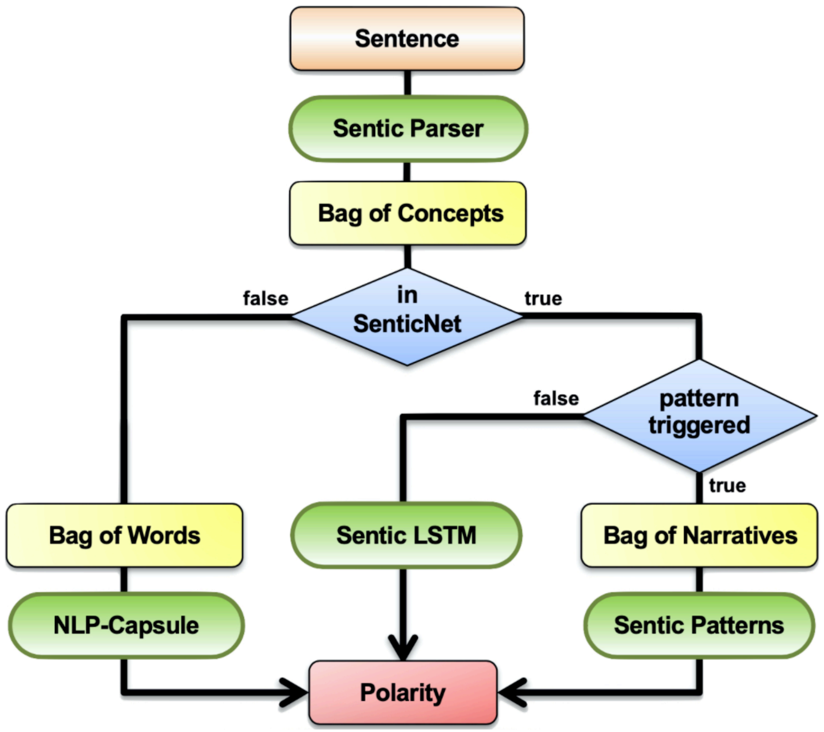
- Introduction
  - Embedded systems for sentiment analysis on the edge
- Image polarity detection on the edge
- Cognitive models and computational resources

Introduction

Sentiment analysis

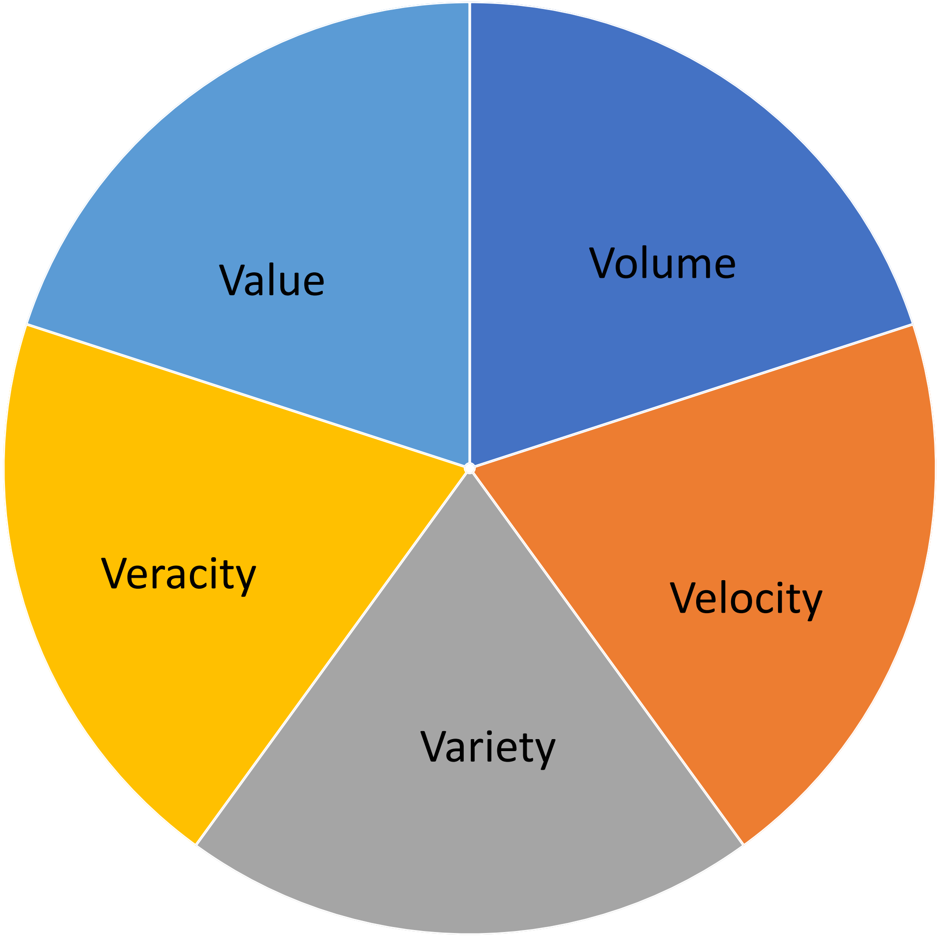
- Sentiment analysis infers users' emotions automatically
  - Traditional artificial intelligence
    - Small computing power
    - Handcrafted feature sets
  - Deep learning
    - High computing power
    - Automatic feature learning

Sentiment analysis: text

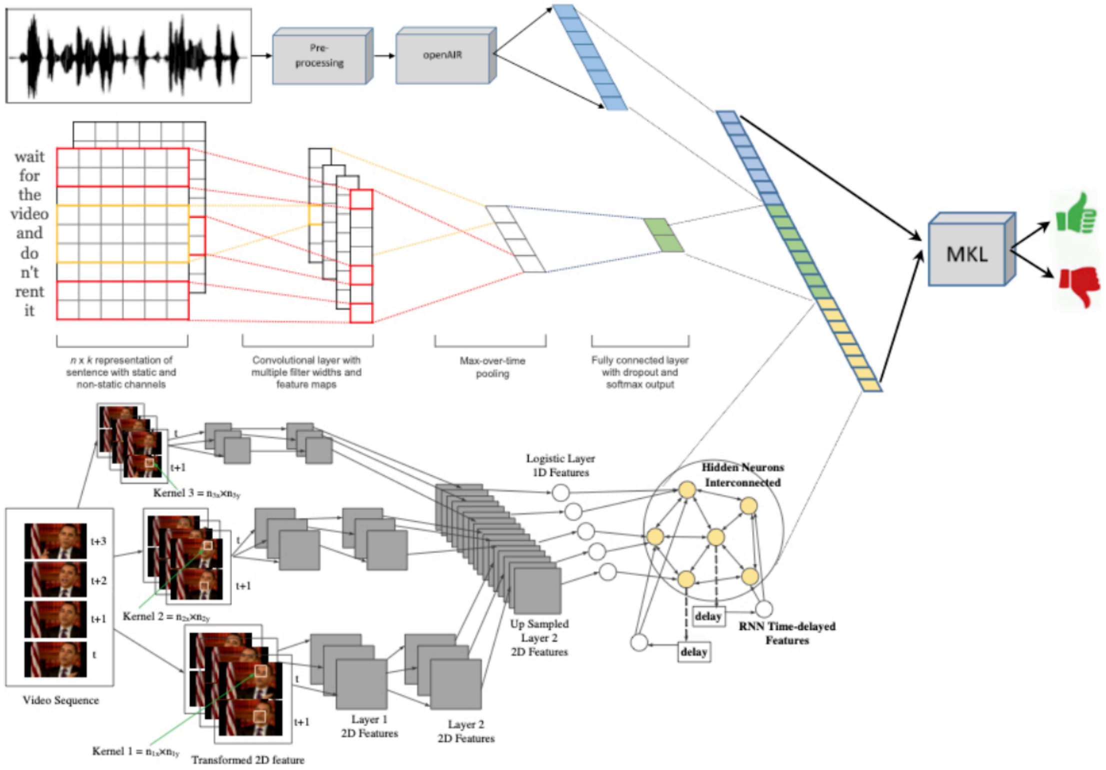


Cambria, E., & Hussain, A. (2012). Sentic computing. *marketing*, *59*(2), 557-577.

Big data era



Sentiment Analysis: multimodal



Poria, S., Chaturvedi, I., Cambria, E., & Hussain, A. (2016, December). Convolutional MKL based multimodal emotion recognition and sentiment analysis. In *2016 IEEE 16th international conference on data mining (ICDM)* (pp. 439-448). IEEE.

Sentiment Analysis: hardware

- Smart
  - Phones
  - Watches
  - Speakers
  - Cameras
  - TVs
  - Glasses
  - Cars
  - Refrigerators

Sentiment Analysis: hardware

- Platforms for deep learning on embedded devices:
    - ***Nvidia Jetson***
    - Movidius
    - Google Colab
    - STM32
    - NPUs
    - VPUs

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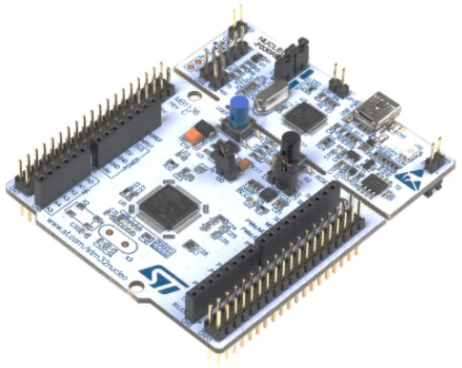

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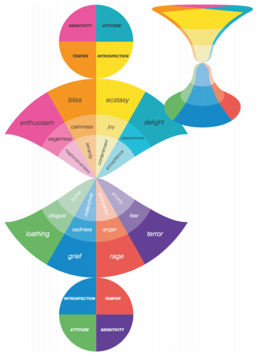
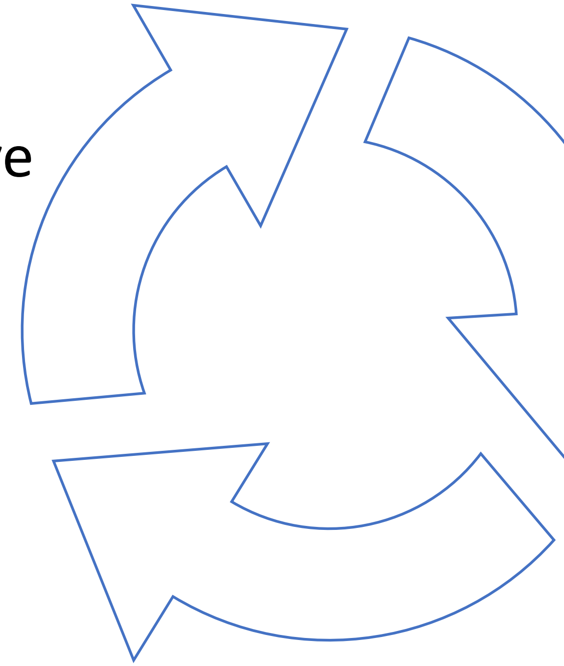
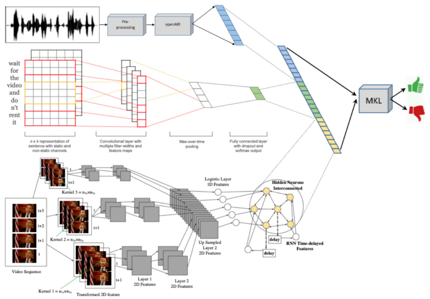
Hardware-algorithm loop



Cognitive
models

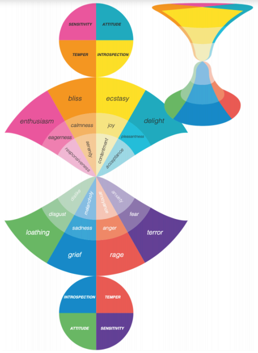


Artificial
Intelligence



Hardware
Resources

Hardware-algorithm loop



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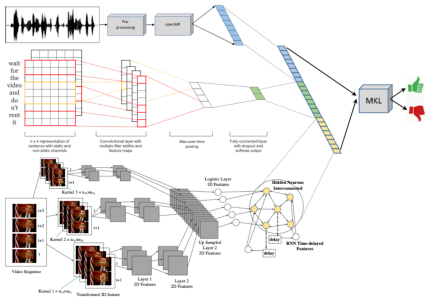

Hardware Resources

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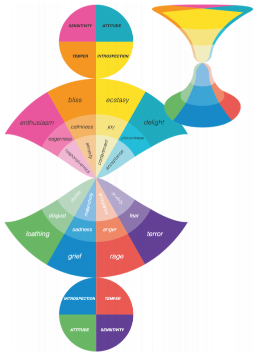

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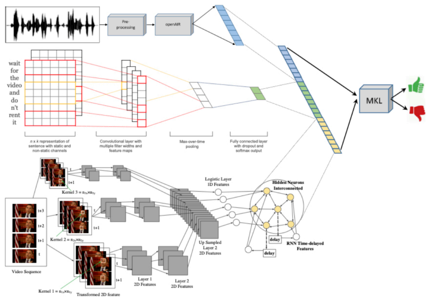

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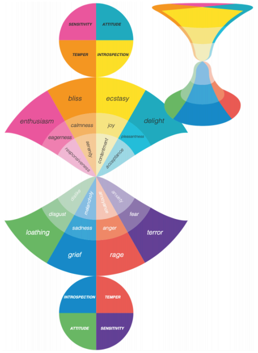

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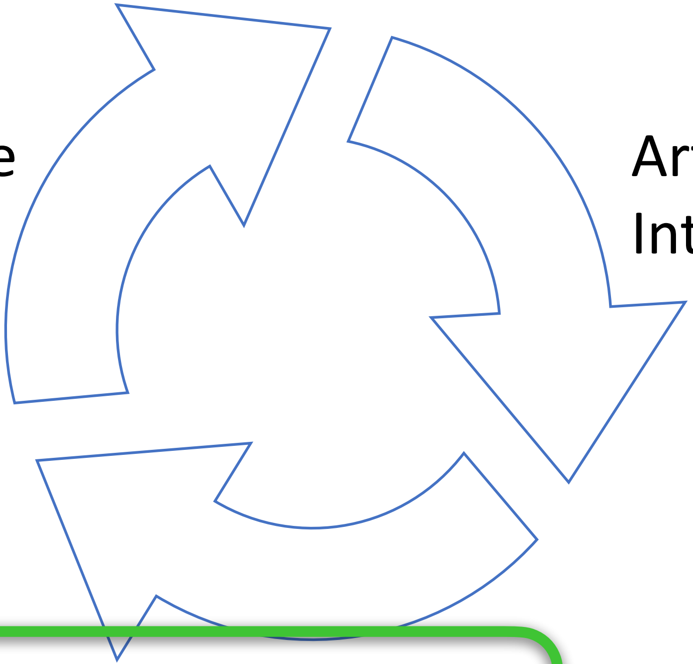

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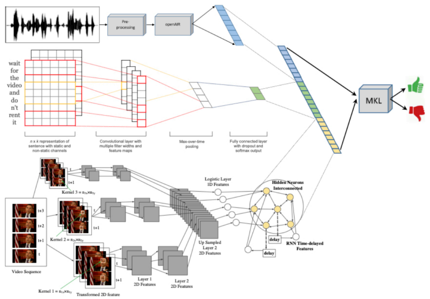

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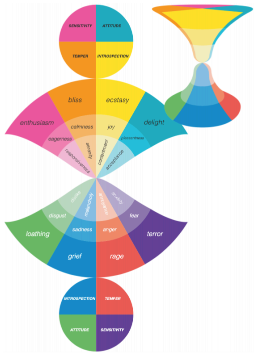

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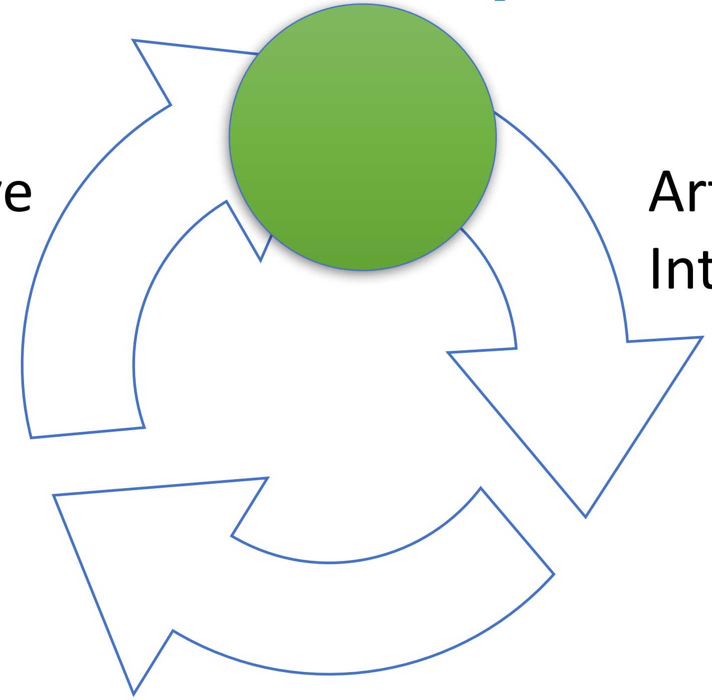

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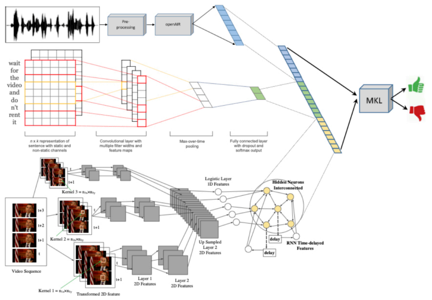

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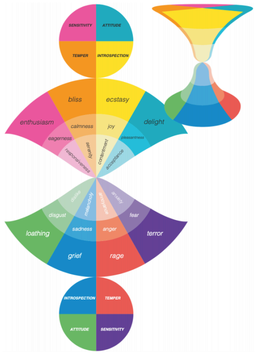

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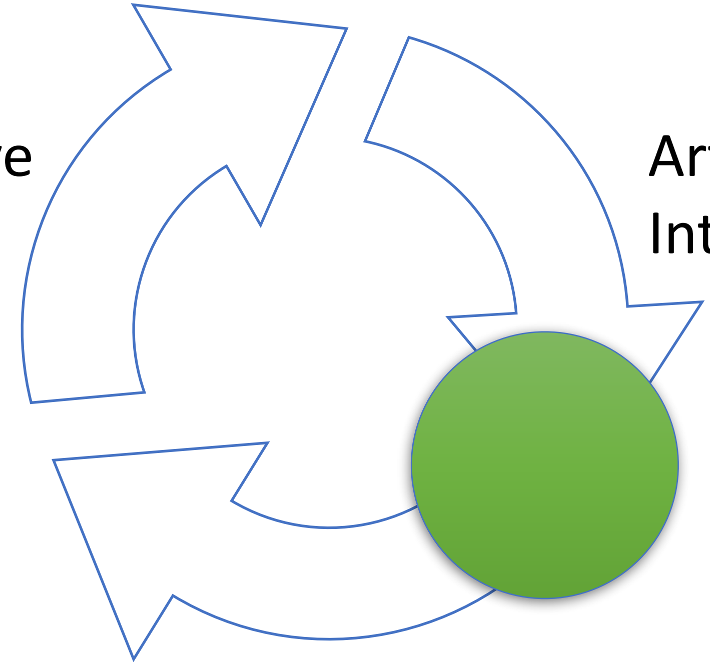

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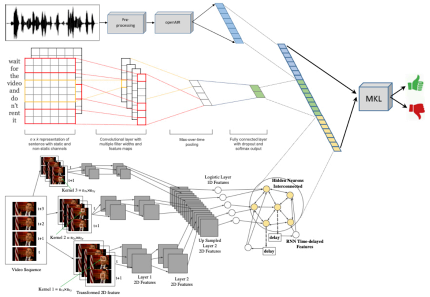

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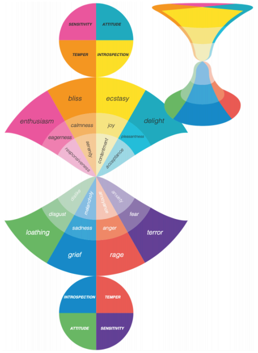

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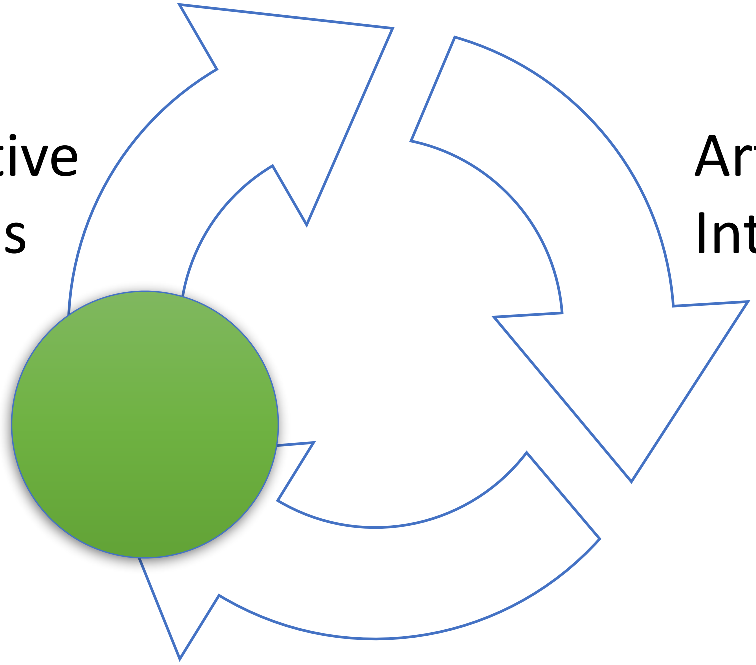

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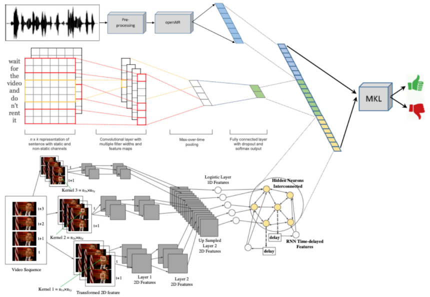

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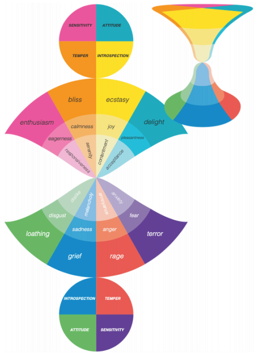

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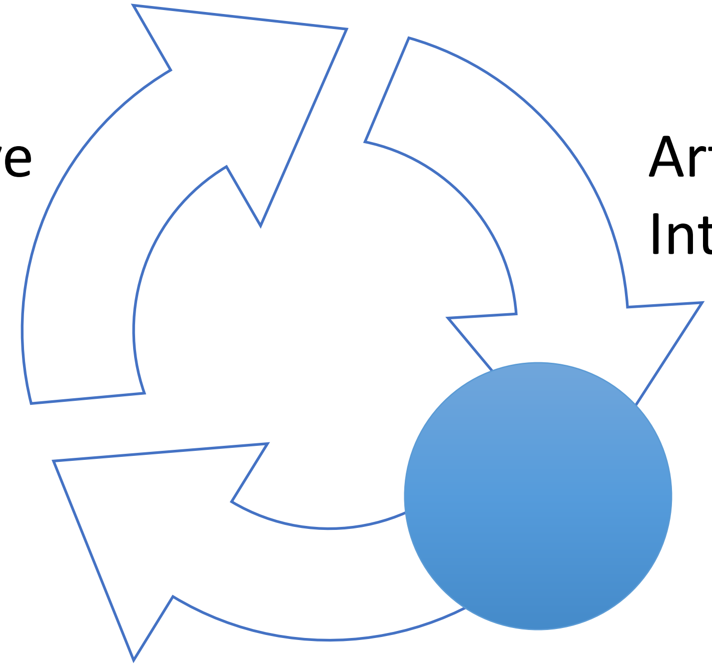

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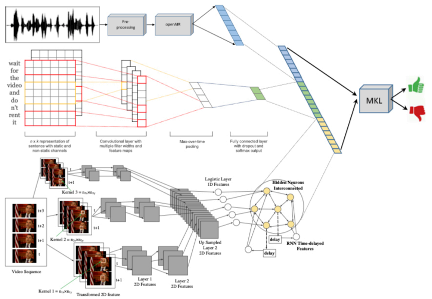

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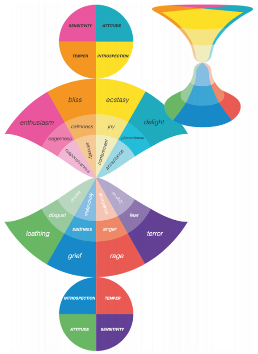

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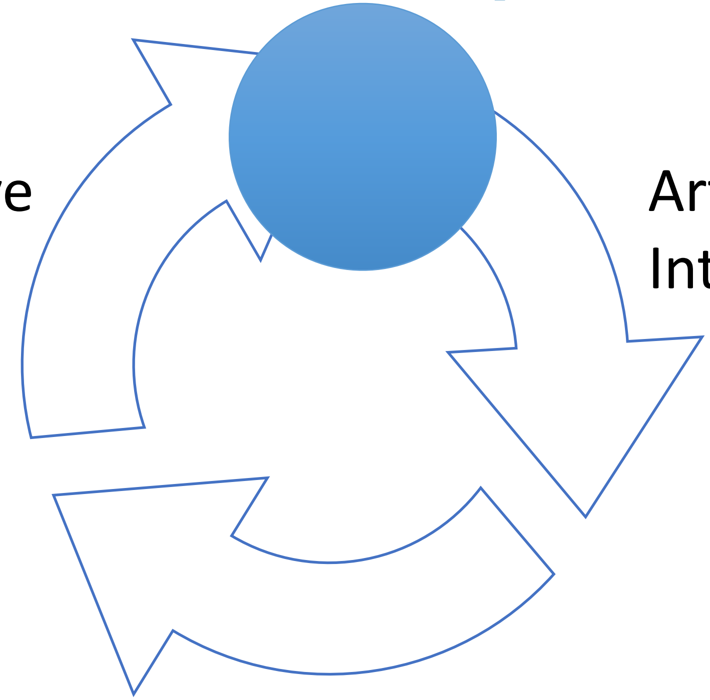

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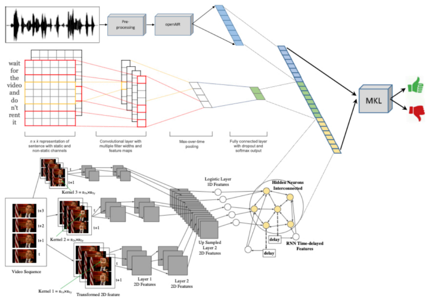

Hardware Resources

Image polarity detection on the edge

Image polarity detection

- ***Polarity***, also known as orientation is the emotion expressed in a content. Usually, it is expressed as positive, negative or neutral.

Image polarity detection

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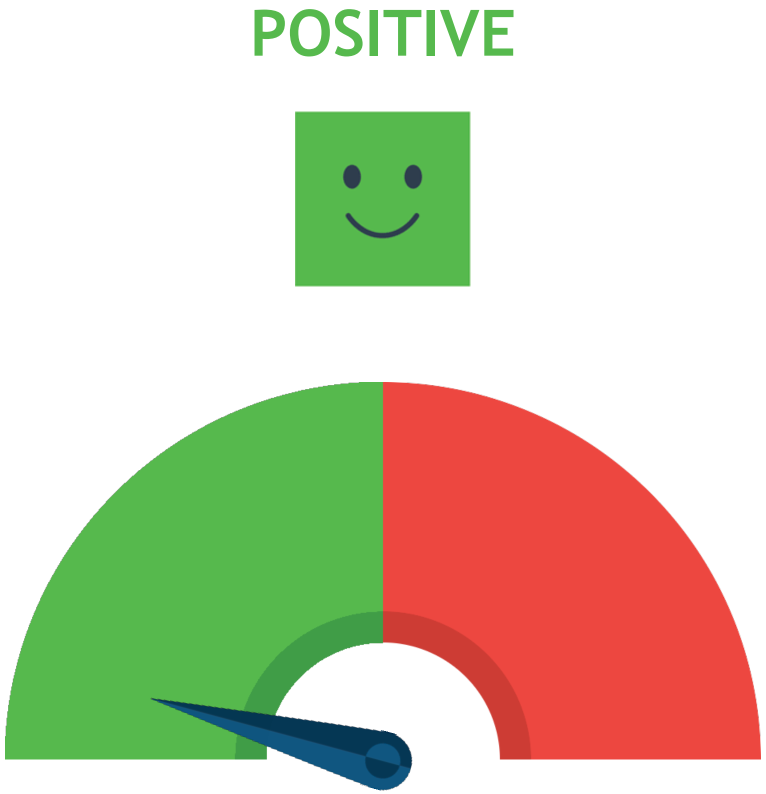

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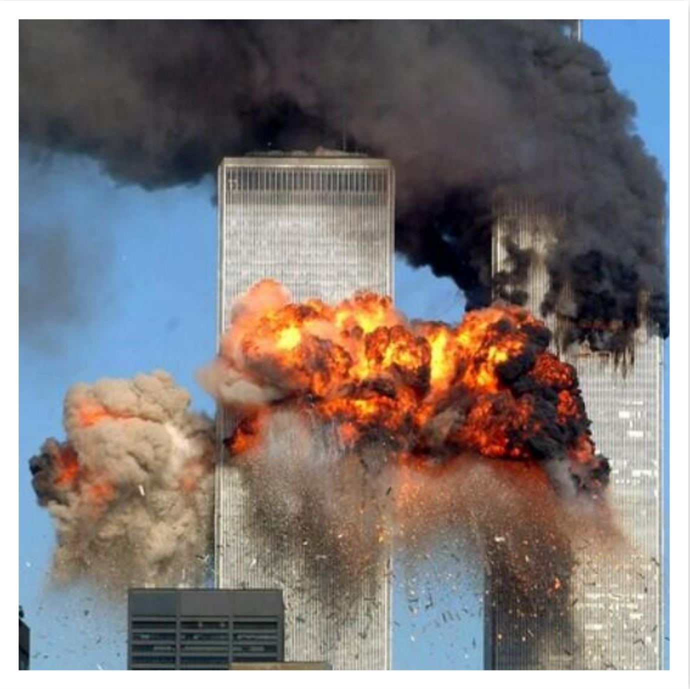

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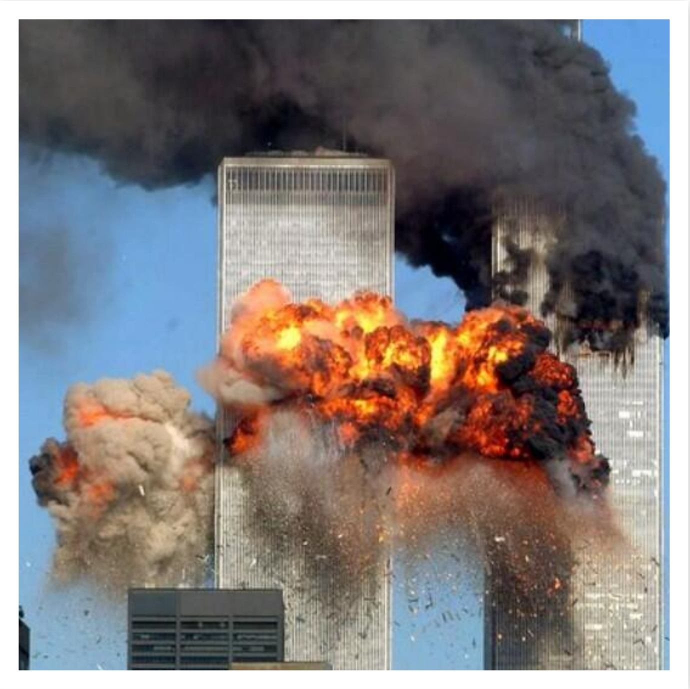
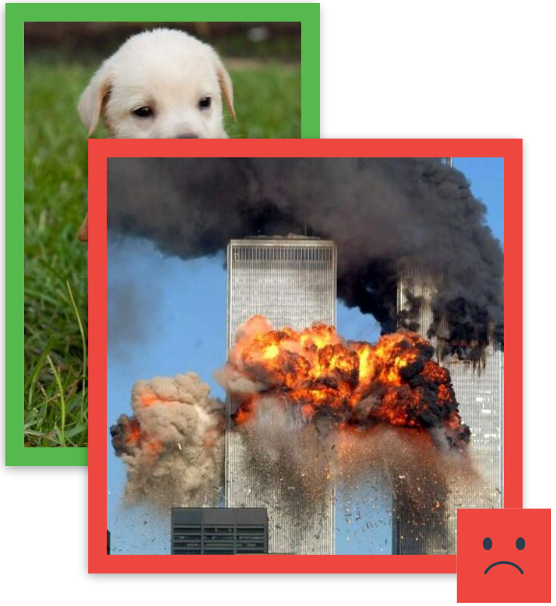


NEGATIVE

Image polarity detection



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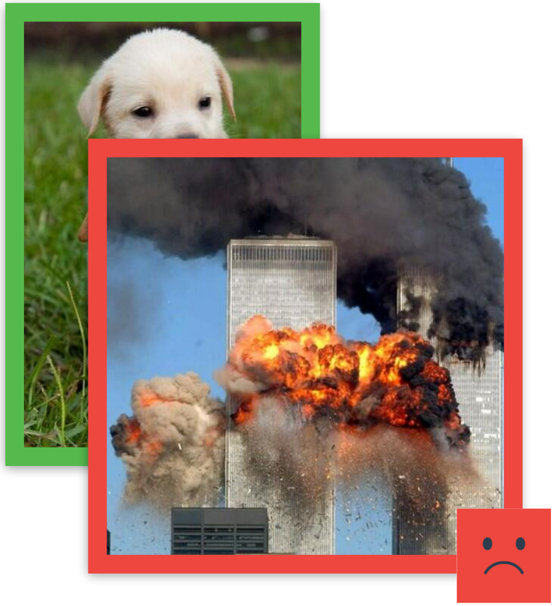

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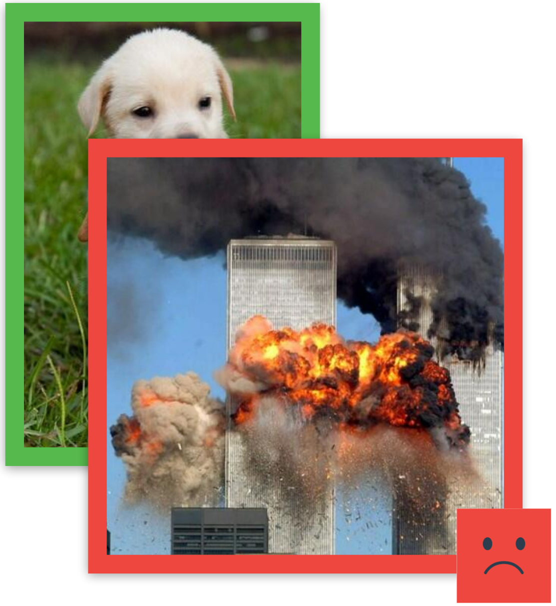


Applications

- Rehabilitation
- Health care systems
- Driving assistance
- Human robot interaction
- Security
- Aiding devices

Why sentiments analysis on the edge

- Cloud computing
  - Strong internet connections
  - High performance hardware on server-side
  - Privacy concerns
    - sensitive information
    - low information about data storage and management

- Smart devices
  - Real-time
  - Low power
  - Safer from the privacy point of view

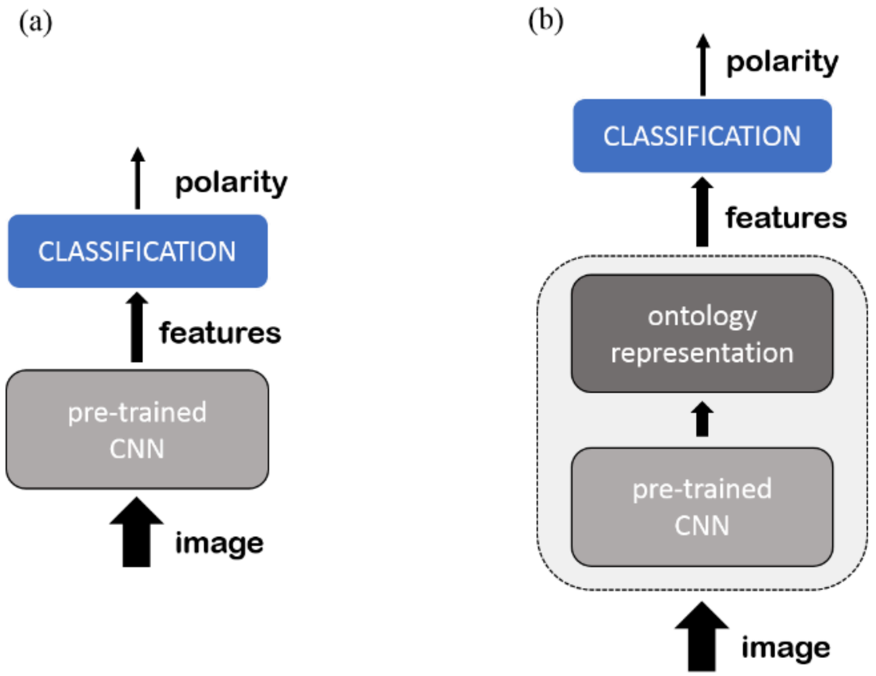
CNNs

- State-of-the-art for all image processing tasks:
  - Image Classification
  - Object Detection

- Drawbacks:
  - Training phase
  - Hardware deployment
    - Power-hungry
    - Memory demanding

Baseline approach

- Fine tune object detection architectures



Ragusa, E., Cambria, E., Zunino, R., & Gastaldo, P. (2019). A survey on deep learning in image polarity detection: Balancing generalization performances and computational costs. *Electronics*, *8*(7), 783.

Object classification architecture

Architecture	Weight Layers	Acc (%)	Operations (Gflops)	Parameters ($\cdot 10^6$)
AlexNet [26]	8	54	**0.7**	61
Vgg_16 [27]	16	71	15.5	138
Vgg_19 [27]	19	71	19.6	144
GoogLeNet [28]	58	68	1.6	**7**
Inc_v3 [29]	46	78	6	24
Res_50 [31]	50	76	3.9	26
Res_101 [31]	101	77	7.6	45
Res_152 [31]	152	79	11.3	60
DenseNet [32]	201	77	4.0	20

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Object classification architecture

Name	Size	Positive Samples	Negative Samples
Tw [12]	882	581	301
Mv_a [74]	702	351	351
Mv_b [74]	702	351	351
ANP40 [22]	17114	11857	5257

Ragusa, E., Cambria, E., Zunino, R., & Gastaldo, P. (2019). A survey on deep learning in image polarity detection: Balancing generalization performances and computational costs. *Electronics*, *8*(7), 783.

Object classification polarity detection

Architecture	**Tw**(882)	**Mv_a**(702)	**Mv_b**(702)	**ANP40**(17K)
AlexNet	82.5 (0.6)	66.2 (0.5)	65.4 (0.7)	76.3 (0.3)
Vgg_16	86.6 (0.4)	68.9 (1.0)	70.7 (1.0)	79.0 (0.3)
Vgg_19	86.4 (0.5)	69.2 (0.7)	**71.0** (0.8)	78.7 (0.3)
GoogLeNet	84.2 (0.5)	66.0 (0.6)	68.2 (0.5)	79.2 (0.3)
Inc_v3	86.5 (0.7)	68.1 (0.7)	70.5 (0.9)	**79.9** (0.2)
Res_50	85.8 (0.6)	68.9 (0.9)	68.8 (1.5)	79.2 (0.2)
Res_101	88.2 (0.4)	70.8 (0.6)	69.2 (0.8)	79.7 (0.2)
DenseNet	**89.4** (0.5)	**71.3** (0.8)	70.6 (0.6)	79.3 (0.3)

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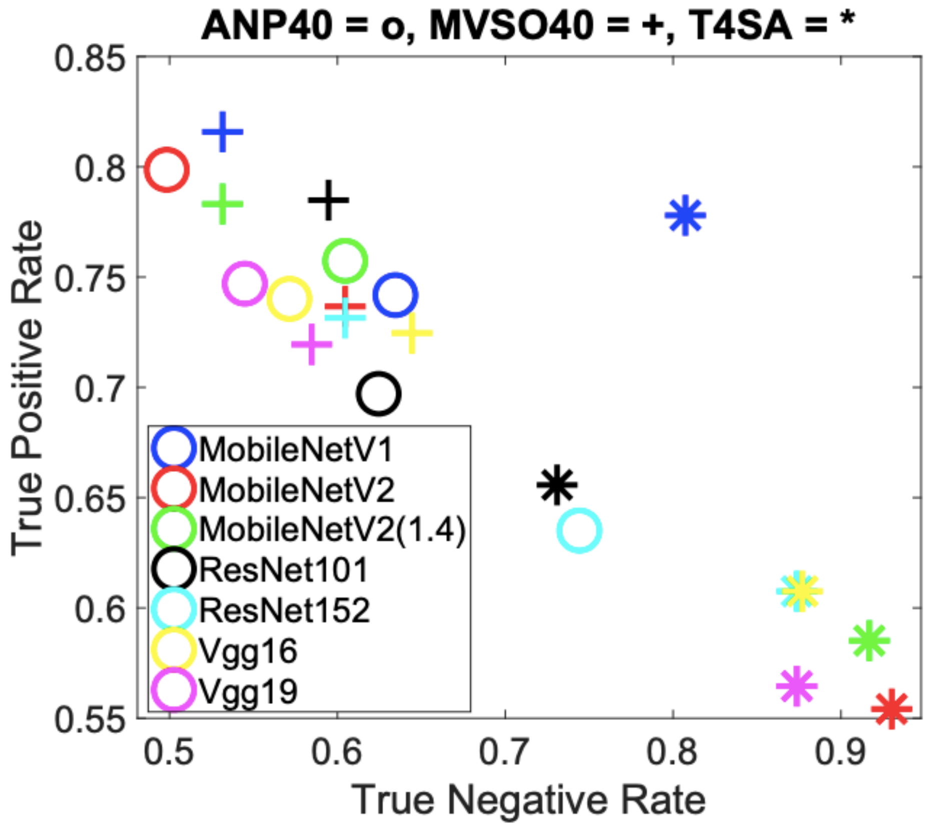
MobileNets for Image Polarity detection

- Mobile nets
  - Key-point: Depth-wise separable convolutions
  - Pros
    - Very high trade-off accuracy/compute cost
    - Explicitly designed for embedded systems
  - Contra
    - Lower accuracy for standard benchmark
      - Object classification
      - Object detection

Howard, A., Sandler, M., Chu, G., Chen, L. C., Chen, B., Tan, M., ... & Le, Q. V. (2019). Searching for mobilenetv3. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 1314-1324).

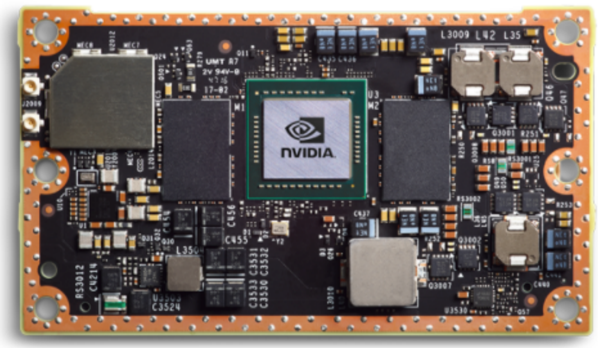
MobileNets for Image Polarity detection



Ragusa, E., Gianoglio, C., Zunino, R., & Gastaldo, P. (2020). Image Polarity Detection on Resource-Constrained Devices. *IEEE Intelligent Systems*.

Edge Accelerators

Jetson TX2



Movidius NCS

Implementation

	Movidius			Jetson		
Architecture	Latency (ms)	Memory (GB)	Power (Watt)	Latency (ms)	Memory (GB)	Power (Watt)
MobileNet_v1	43.98	0.18	1.17	12.0	0.93	1.65/5.76
MobileNet_v2	43.40	0.17	0.87	16.3	2.56	2.04/6.13
MobileNet_v2(1.4)	61.59	0.20	1.20	24.2	3.69	2.12/6.37
Res_101	405.49	0.93	1.42	22.2	4.22	1.56/7.55
Res_152	607.26	1.23	1.56	31.7	8.42	1.55/7.71
Vgg_16	864.84	2.68	-	43.7	11.60	2.41/7.94
Vgg_19	1046.84	2.79	-	58.0	11.59	2.38/7.59

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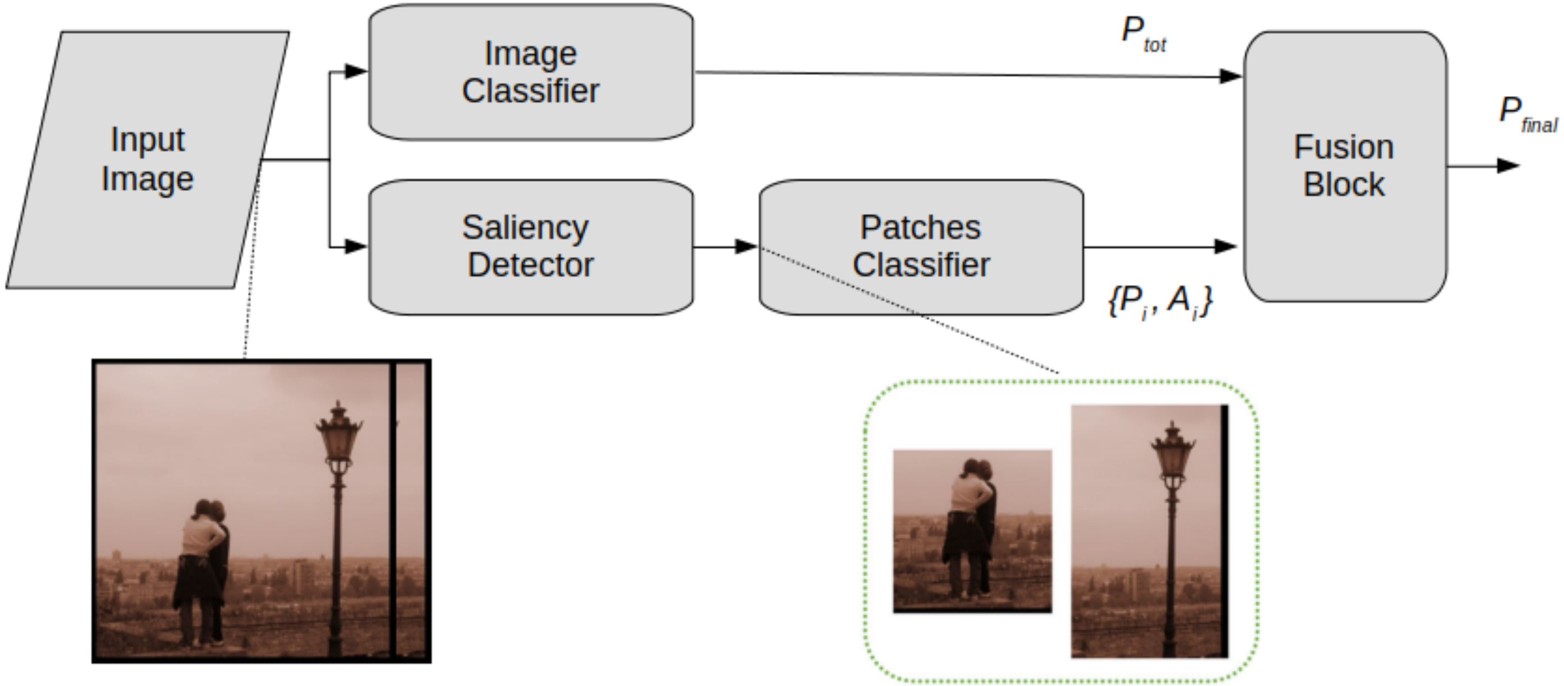
Role of saliency

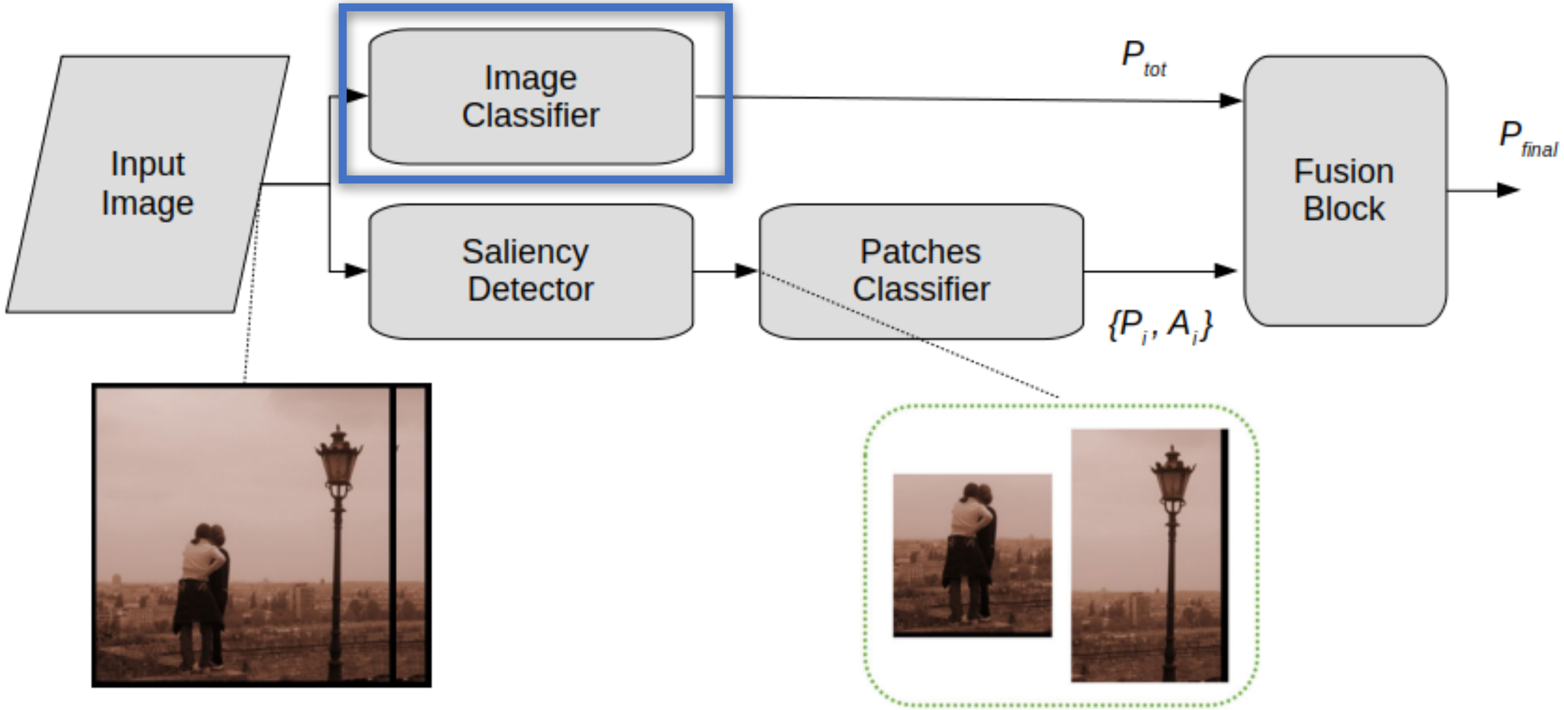
Role of saliency

Proposal

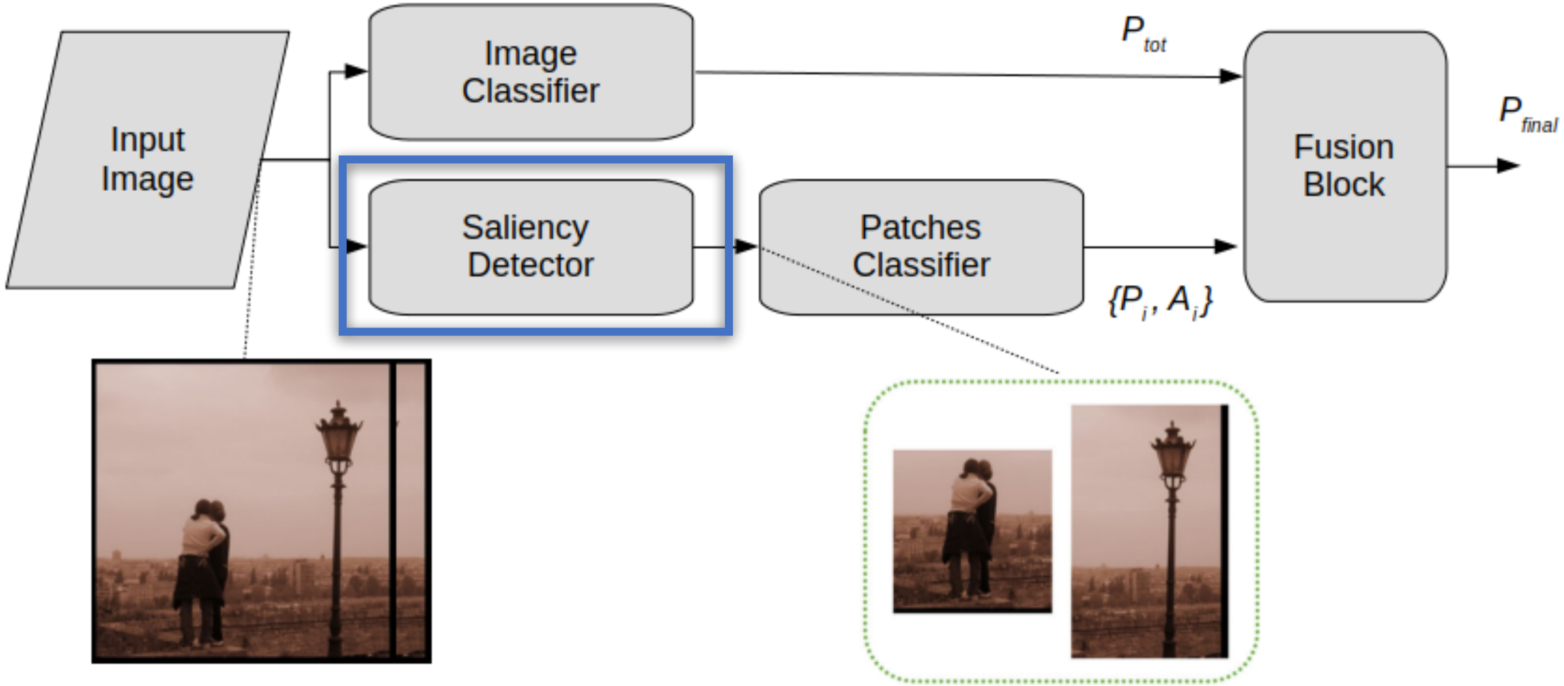


Ragusa, E., Apicella, T., Gianoglio, C., Zunino, R., & Gastaldo, P. (2020). An hardware-aware image polarity detector enhanced with visual attention. *IJCNN 2020, accepted*

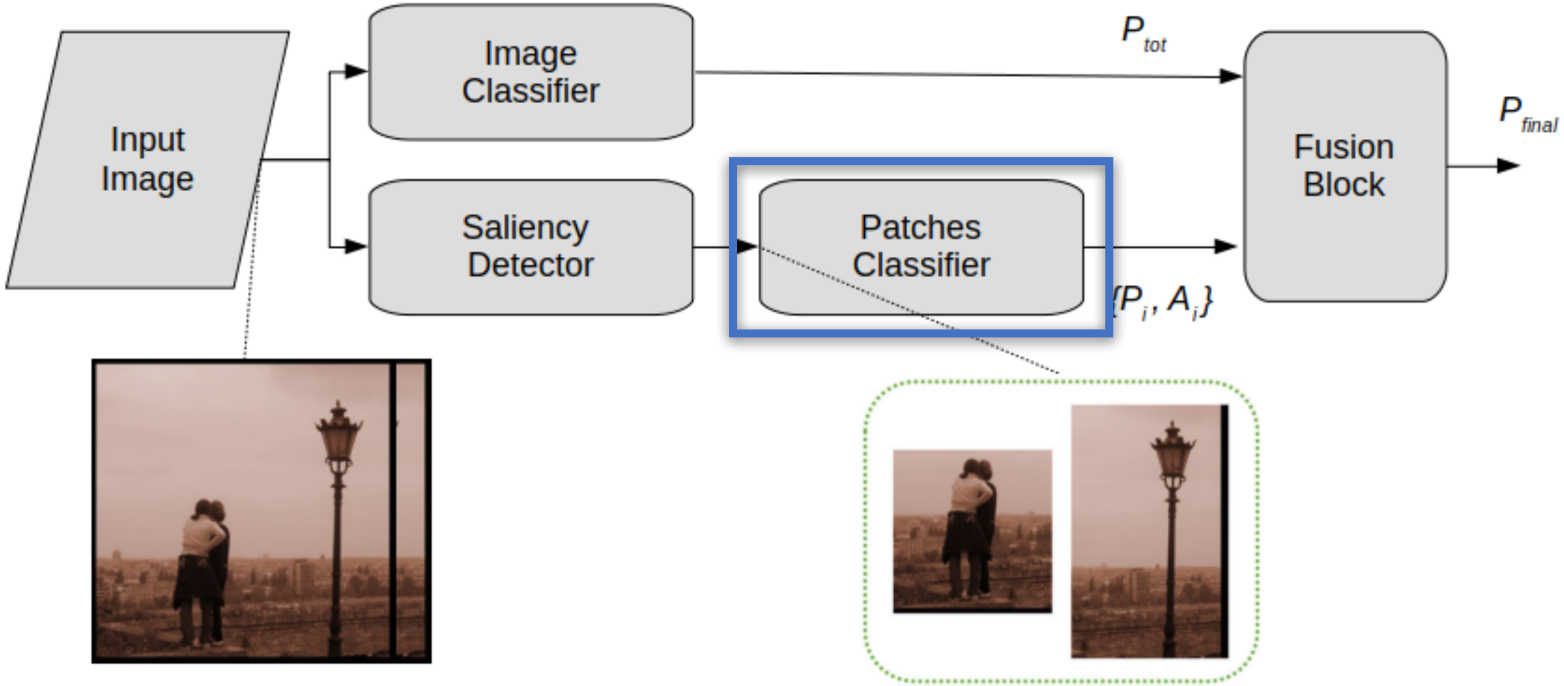
Proposal


Input
Image
Image
Classifier
Saliency
Detector
Patches
Classifier
P_{tot}
$\{P_i, A_i\}$
Fusion
Block
P_{final}

Proposal

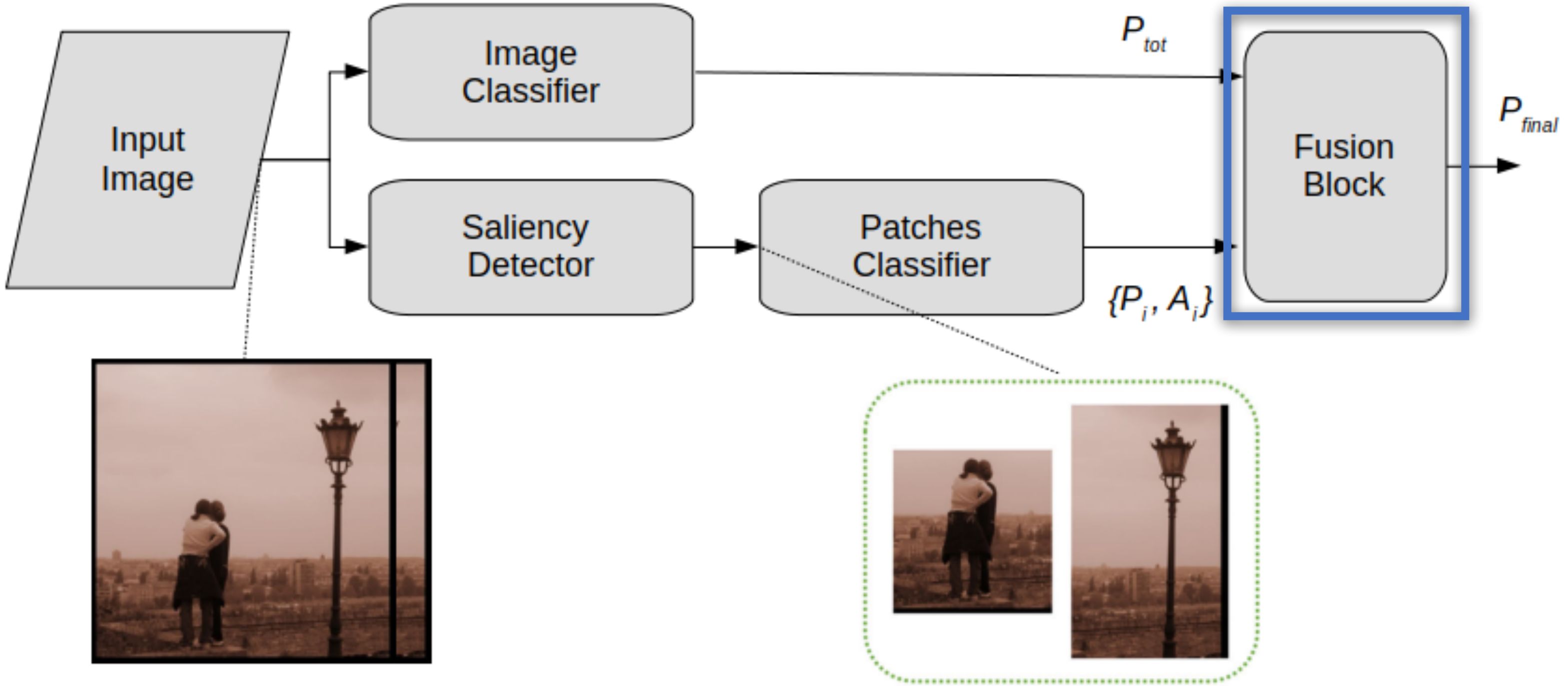

Input Image
Image Classifier
Saliency Detector
Patches Classifier
Fusion Block
P_{tot}
P_{final}
$\{P_i, A_i\}$

Proposal



Input Image
Image Classifier
Saliency Detector
Patches Classifier
P_{tot}
Fusion Block
P_{final}
$\{P_i, A_i\}$

Proposal

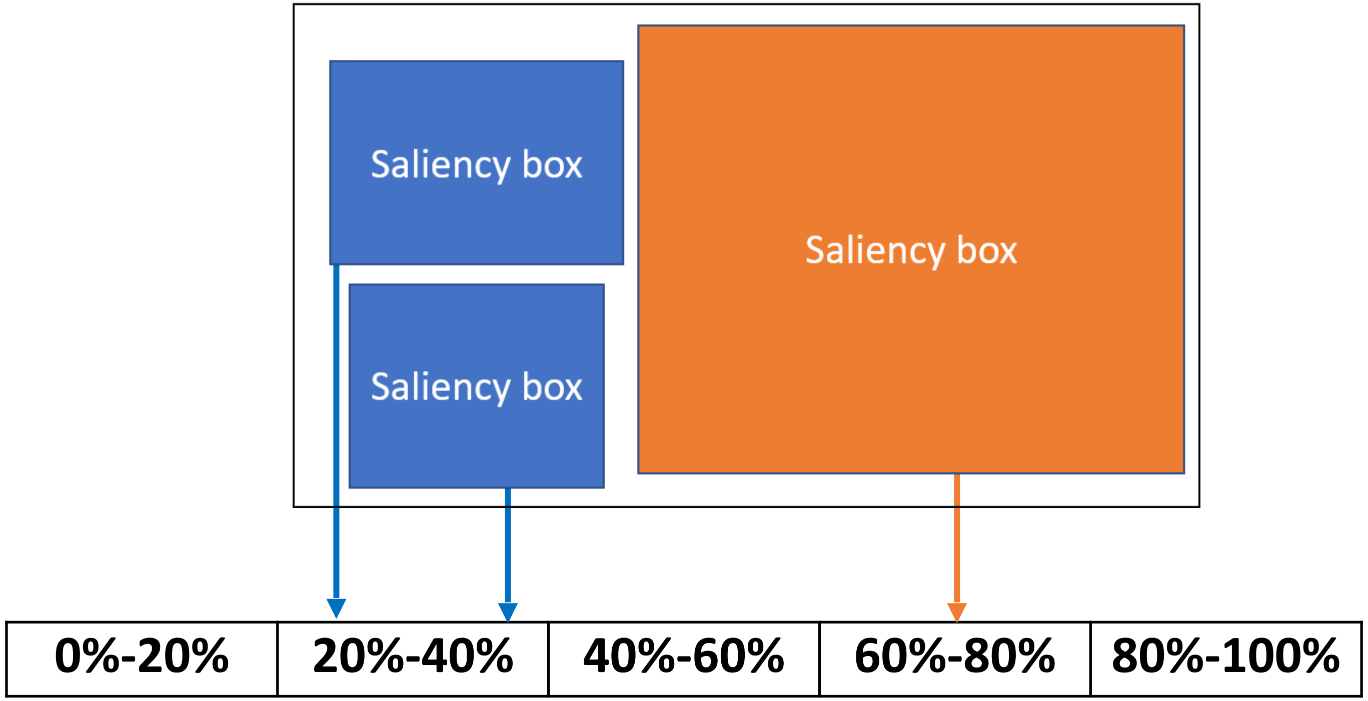

Input Image
Image Classifier
Saliency Detector
Patches Classifier
P_{tot}
$\{P_i, A_i\}$
Fusion Block
P_{final}

Blocks

- Image classifier and Patches classifier
  - MobileNetV1
- Saliency detector
  - SSD-MobileNetV1
- Fusion block
  - Rule based

Huang, J., Rathod, V., Sun, C., Zhu, M., Korattikara, A., Fathi, A., ... & Murphy, K. (2017). Speed/accuracy trade-offs for modern convolutional object detectors. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 7310-7311).

Fusion Block



Fusion Block

Name	0%-20%	20%-40%	40%-60%	60%-80%	80%-100%
Imm_x		+0.8		+0.55	
		-0.55			

+0.25

+0.55

Fusion Block

Name	**20%-40%**	**60%-80%**	***Entire image***
Imm_x	+0.8	+0.55	-0.8
	-0.55		

+0.25 +0.55 -0.8

Fusion Block

Name	**20%-40%**	**60%-80%**	***Entire image***
Imm_x	+0.8	+0.55	-0.8
	-0.55		

+0.25 +0.55 -0.8

Experiments

- Saliency detection

- Proposal

- Deployment on smartphones

Saliency detection

- Network
    - SSD MobileNetV1
        - TensorFlow Object Detect API
        - Iterations 50000

- ILSVRC-2014
    - 127030 images
- SOS
    - 3951 images

Results

- Standard hold out:
    - 90% training
    - 10% test

TABLE I
SALIENCY DETECTOR PERFORMANCES

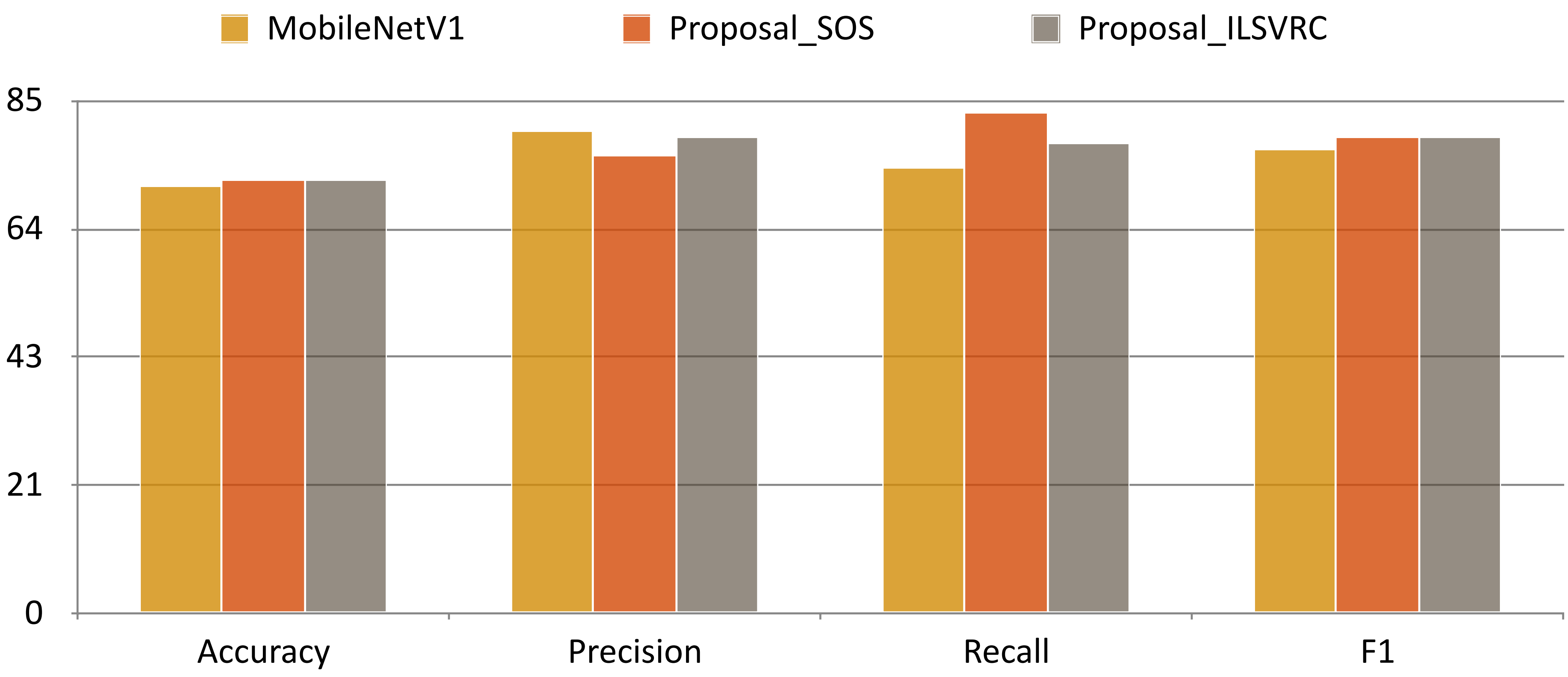
Saliency detector	**True boxes**	**Predicted**	**IoU $> 75\%$**
SSD_MobileNet_ILSVRC	13982	13118	10207
SSD_MobileNet_SOS	13982	14723	9272

Experiments

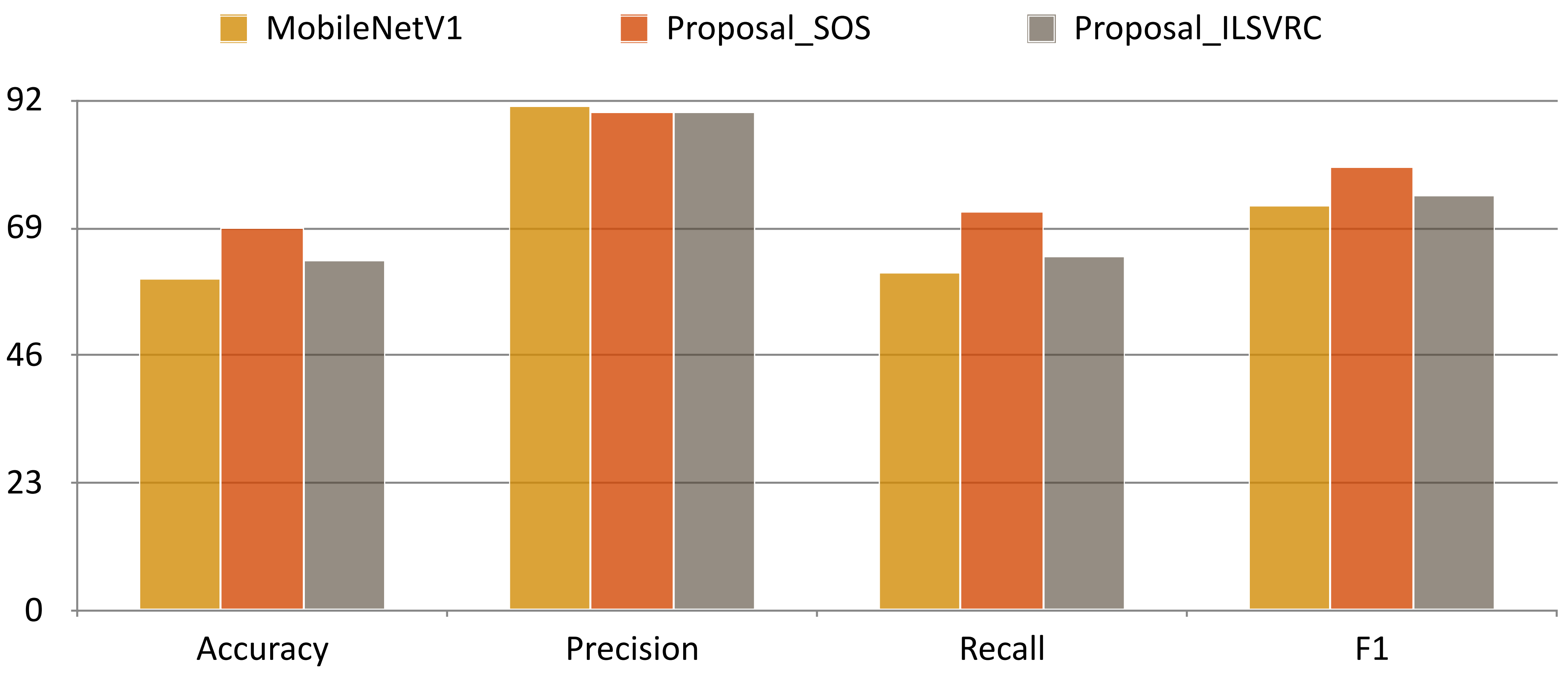
- MobileNetV1
  - TensorFlow-Slim library

- Dataset
  - Training:
    - ANP40
  - Test:
    - Twitter
    - MVSA_eq
    - MVSA_maj

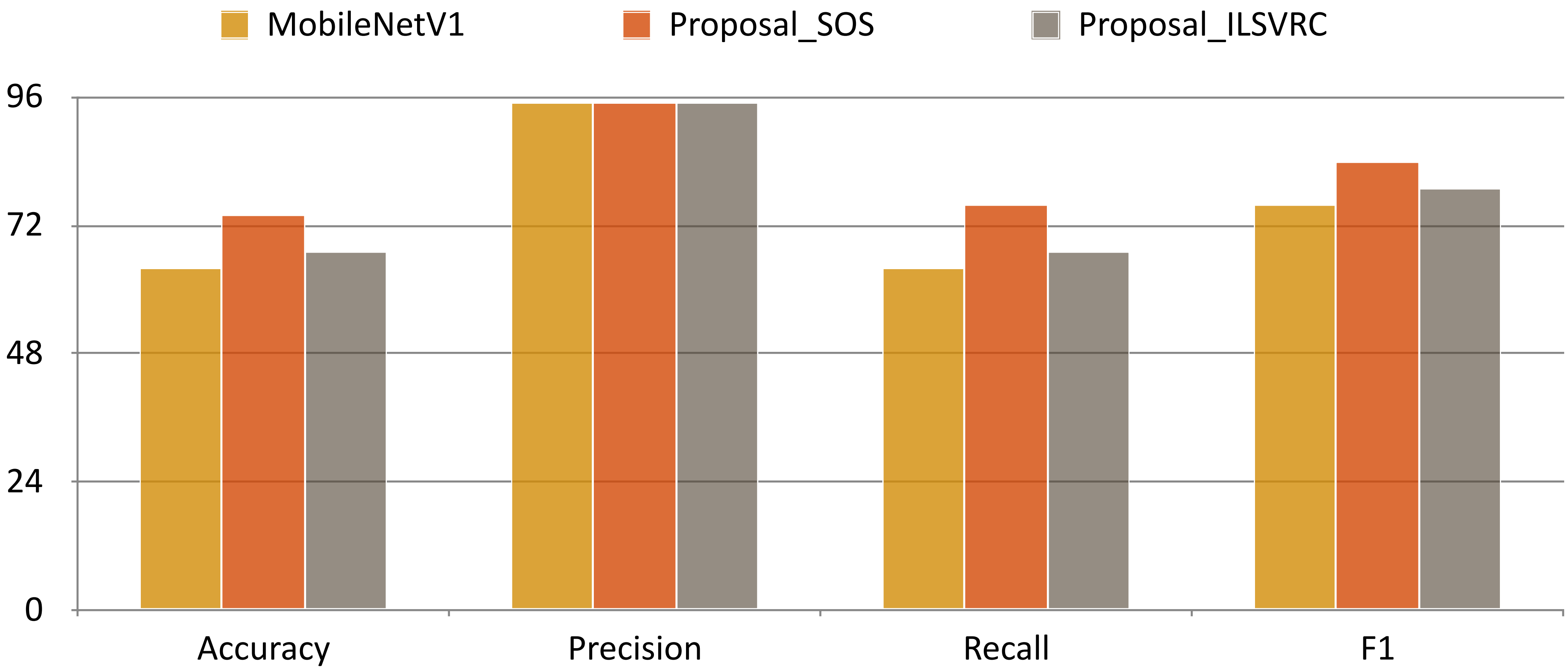
Experiments: Twitter



Experiments: MVSA_maj



Experiments: MVSA_eq



Smartphones Implementation

- 5 android smartphones
    - Only processor
        - No gpu or Npu

- Inference time for an image:
    - 0.5 to 0.9 seconds FP32
    - 0.4 to 0.8 second FP16

Conclusion

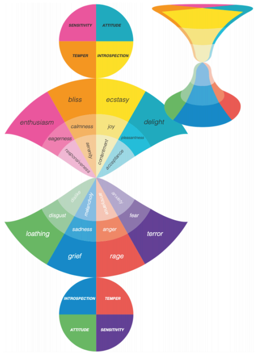
- This part of the speech presented:

  - Strategies, algorithms and hardware devices for image polarity detection on embedded devices

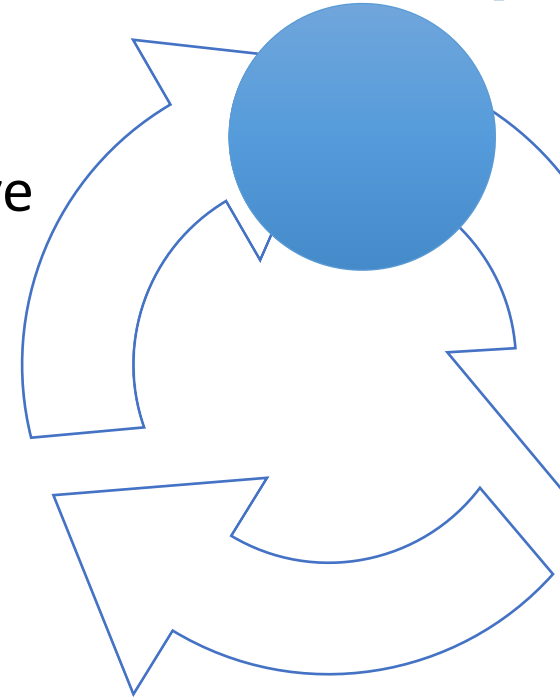
  - Result regarding accuracy and hardware performances.

Cognitive models and computational resources

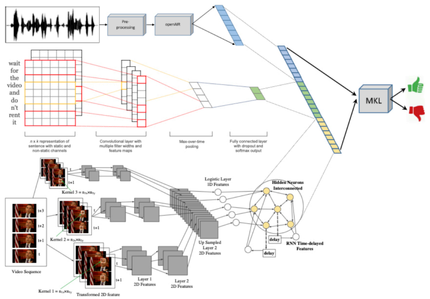
Hardware-algorithm loop



Cognitive models



Artificial Intelligence



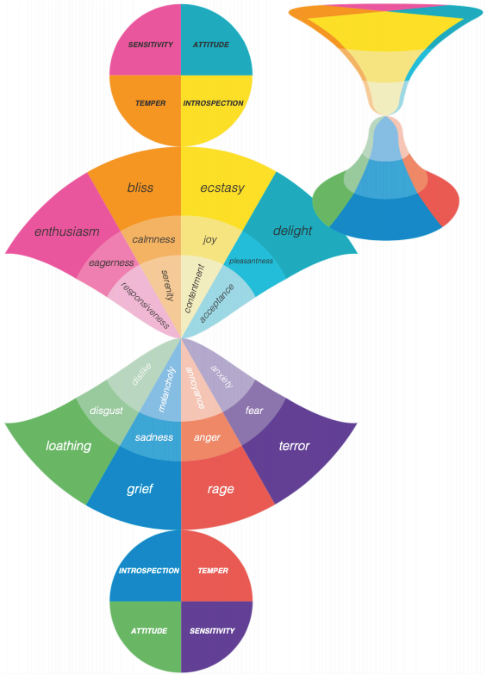
Hardware Resources

Cognitive models and computational resources

- Goal
  - Study the coherence between
    - Cognitive model
      - Hourglass of emotions
    - Computational resource
      - Affective space
- Output
  - Experimental protocol
  - Analysis

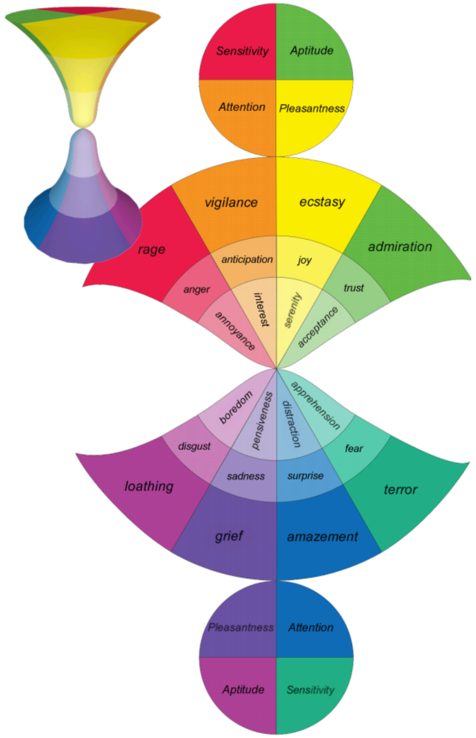
Ragusa, E., Gastaldo, P., Zunino, R., Ferrarotti, M. J., Rocchia, W., & Decherchi, S. (2019). Cognitive Insights into Sentic Spaces Using Principal Paths. *Cognitive Computation*, *11*(5), 656-675.

Cognitive model: The Hourglass of Emotions



Susanto, Y., Livingstone, A., Ng, B. C., & Cambria, E. (2020). The hourglass model revisited. *IEEE Intelligent Systems*, *35*(5).

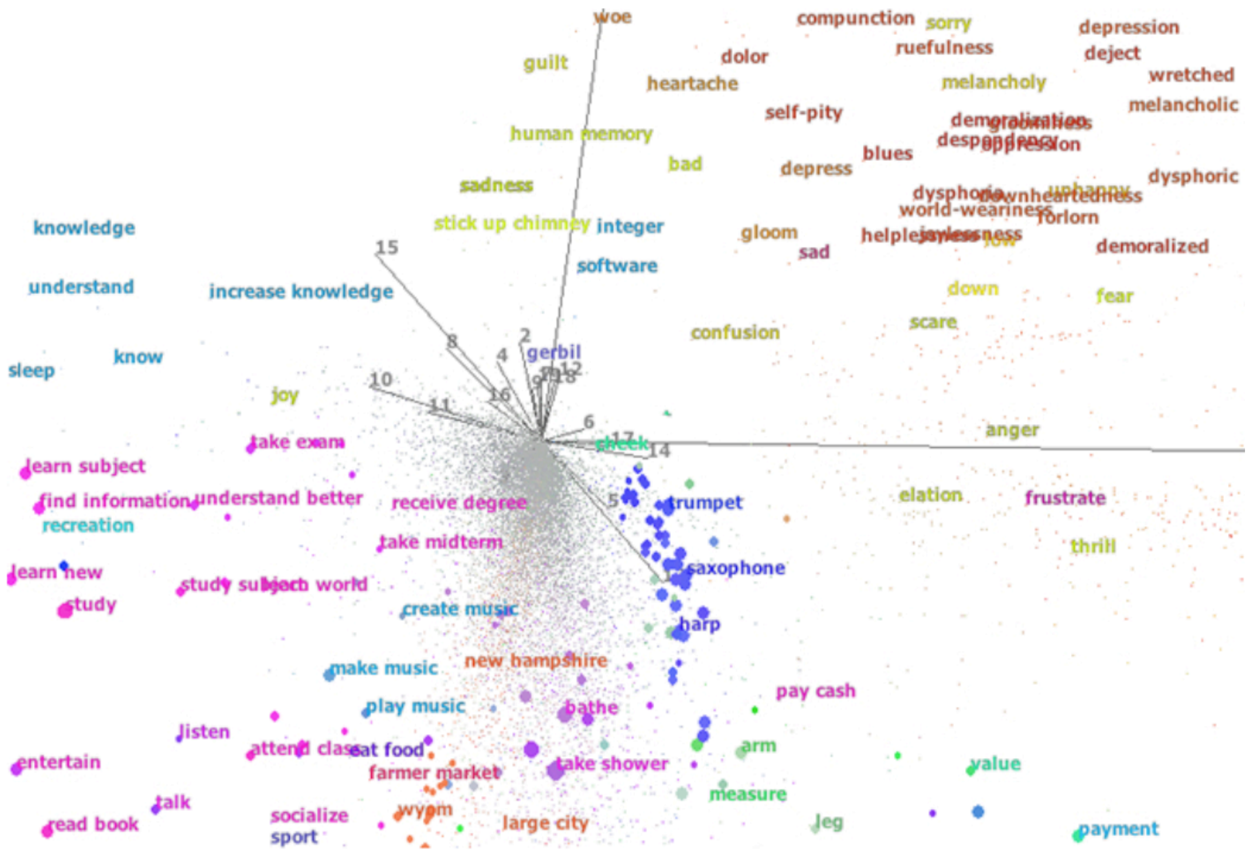
Cognitive model: The Hourglass of Emotions



State of mind → 4 dimensional vector

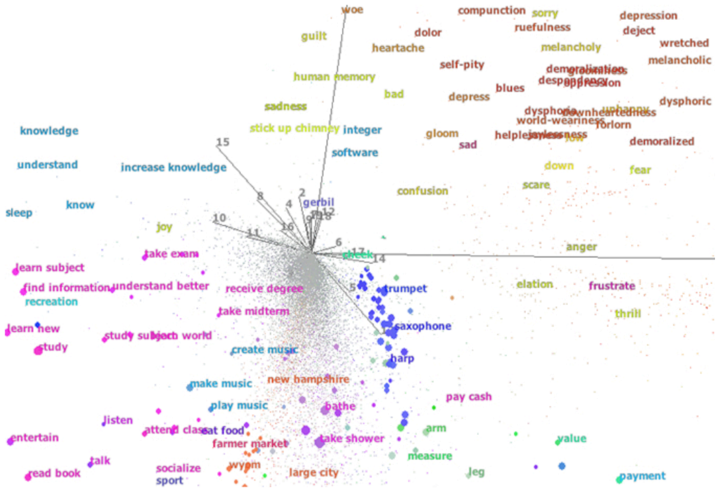
Cambria, E., Livingstone, A., & Hussain, A. (2012). The hourglass of emotions. In *Cognitive behavioural systems* (pp. 144-157). Springer, Berlin, Heidelberg.

Affective Space



Cambria, E., Fu, J., Bisio, F., & Poria, S. (2015, February). AffectiveSpace 2: Enabling affective intuition for concept-level sentiment analysis. In *Twenty-ninth AAAI conference on artificial intelligence*.

Affective Space



Concepts

300 dimensional vectors

Cambria, E., Fu, J., Bisio, F., & Poria, S. (2015, February). AffectiveSpace 2: Enabling affective intuition for concept-level sentiment analysis. In *Twenty-ninth AAAI conference on artificial intelligence*.

Motivation

- Affective space is 300 dimensional
    - Inspection is difficult

- Standard measures cosine/euclidean does not represent completely cognitive models

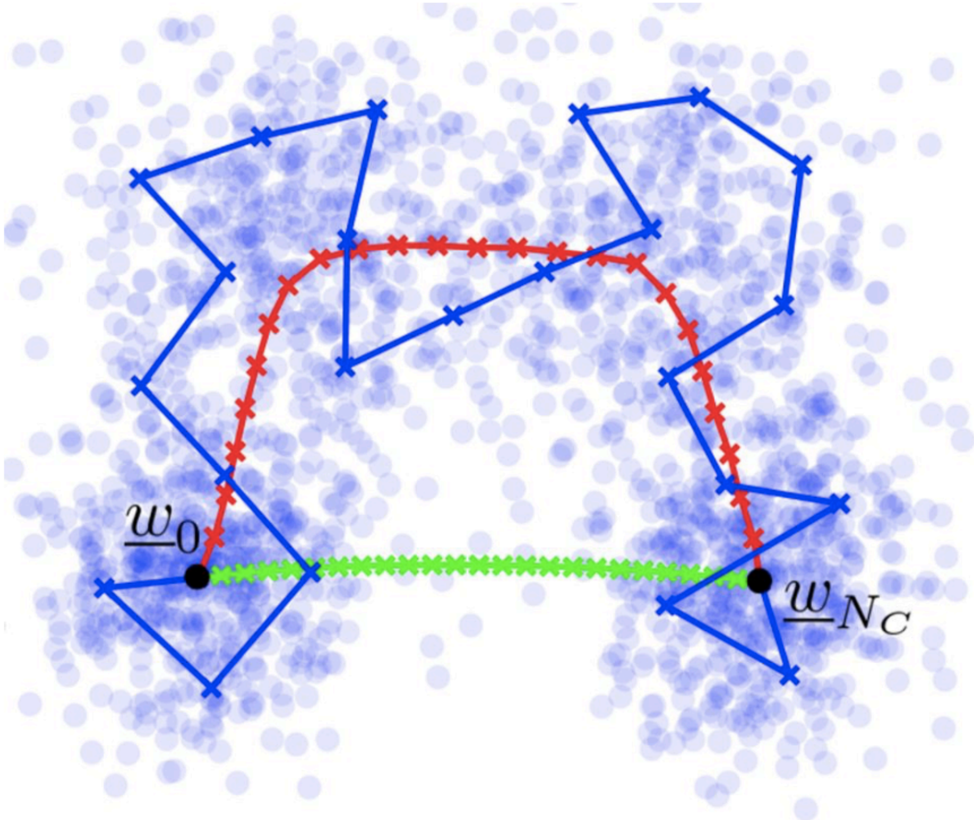
- Dimensionality reduction techniques could be helpful for visualization but limit the insight about the relative position of the data in the 300- dimensional affective space

Principal path algorithm

$$\min_{\boldsymbol{W}} \frac{\gamma}{2} \sum_{i=1}^{N} \sum_{j=1}^{N_c} \|\boldsymbol{x}_i - \boldsymbol{w}_j\|^2 \delta(u_i, j) + \frac{\lambda}{2} \sum_{i=0}^{N_c} \|\boldsymbol{w}_{i+1} - \boldsymbol{w}_i\|^2$$

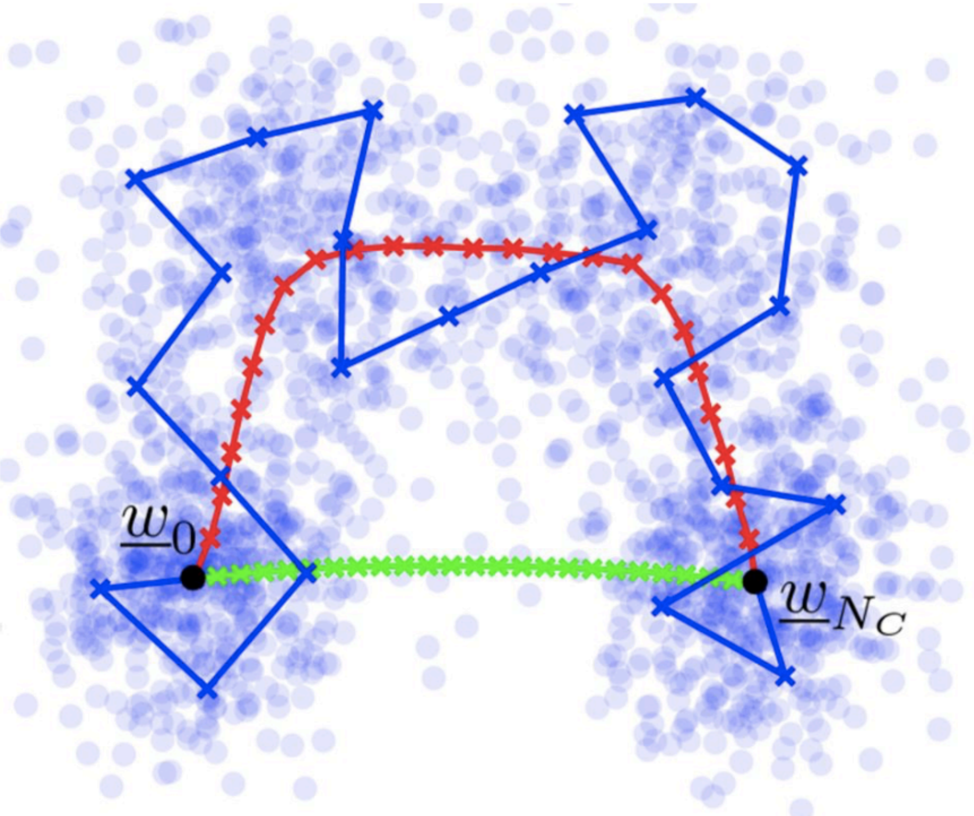
Ferrarotti, M. J., Rocchia, W., & Decherchi, S. (2018). Finding principal paths in data space. *IEEE transactions on neural networks and learning systems*, *30*(8), 2449-2462.

Principal path algorithm



Ferrarotti, M. J., Rocchia, W., & Decherchi, S. (2018). Finding principal paths in data space. *IEEE transactions on neural networks and learning systems*, *30*(8), 2449-2462.

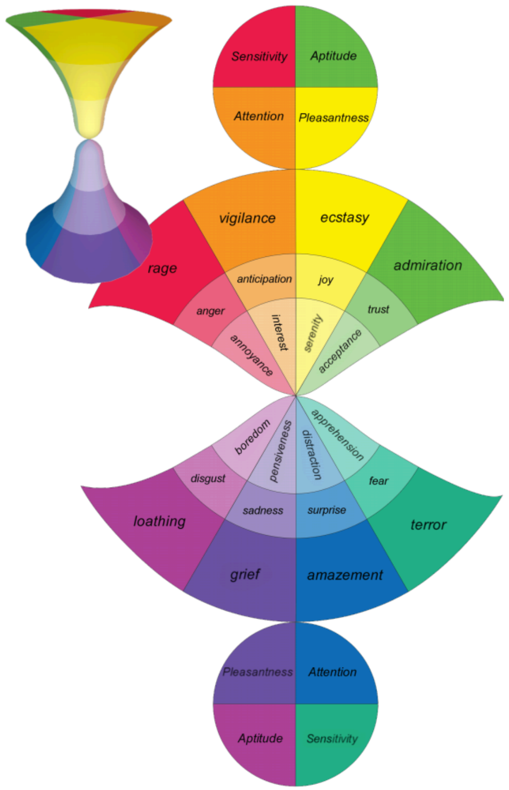
Principal path algorithm

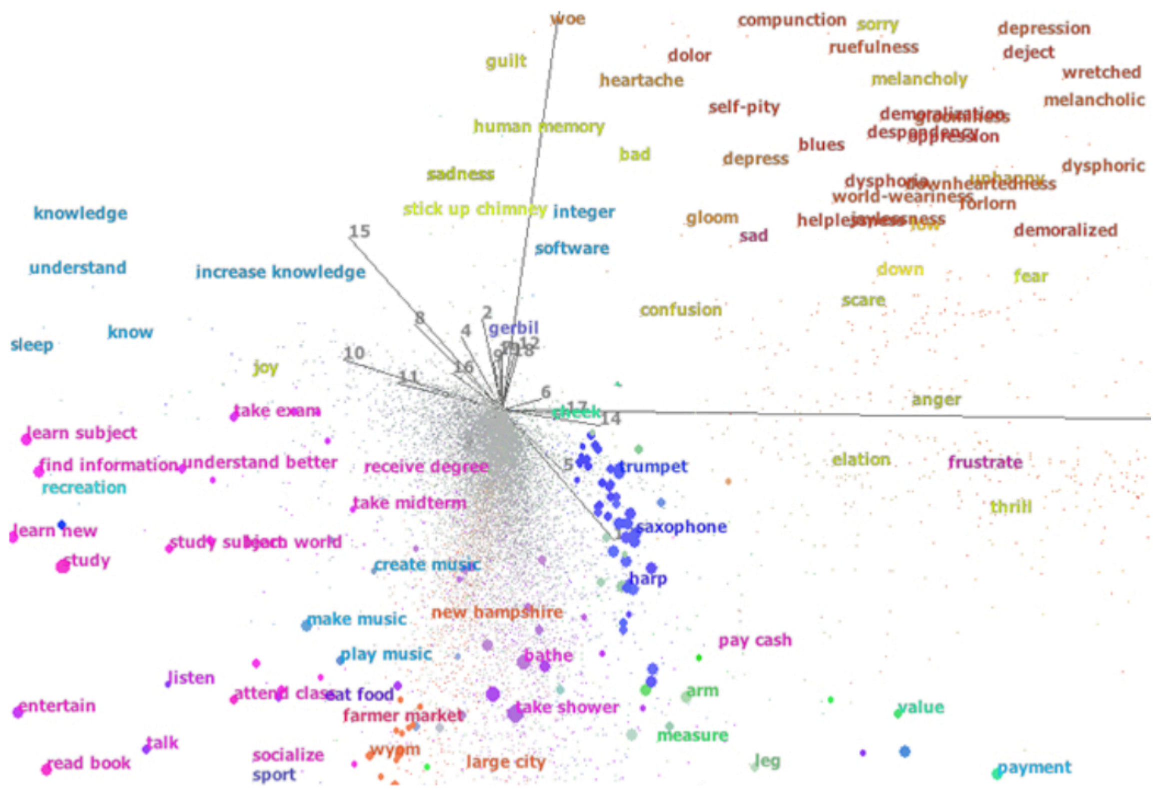


Given two points, it describes data manifolds using a ordered set of points.

Ferrarotti, M. J., Rocchia, W., & Decherchi, S. (2018). Finding principal paths in data space. *IEEE transactions on neural networks and learning systems*, *30*(8), 2449-2462.

Paths in AffectiveSpace



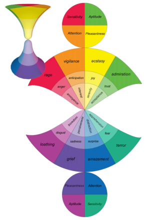


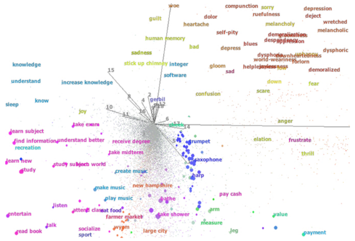
Ragusa, E., Gastaldo, P., Zunino, R., Ferrarotti, M. J., Rocchia, W., & Decherchi, S. (2019). Cognitive Insights into Sentic Spaces Using Principal Paths. *Cognitive Computation*, *11*(5), 656-675.

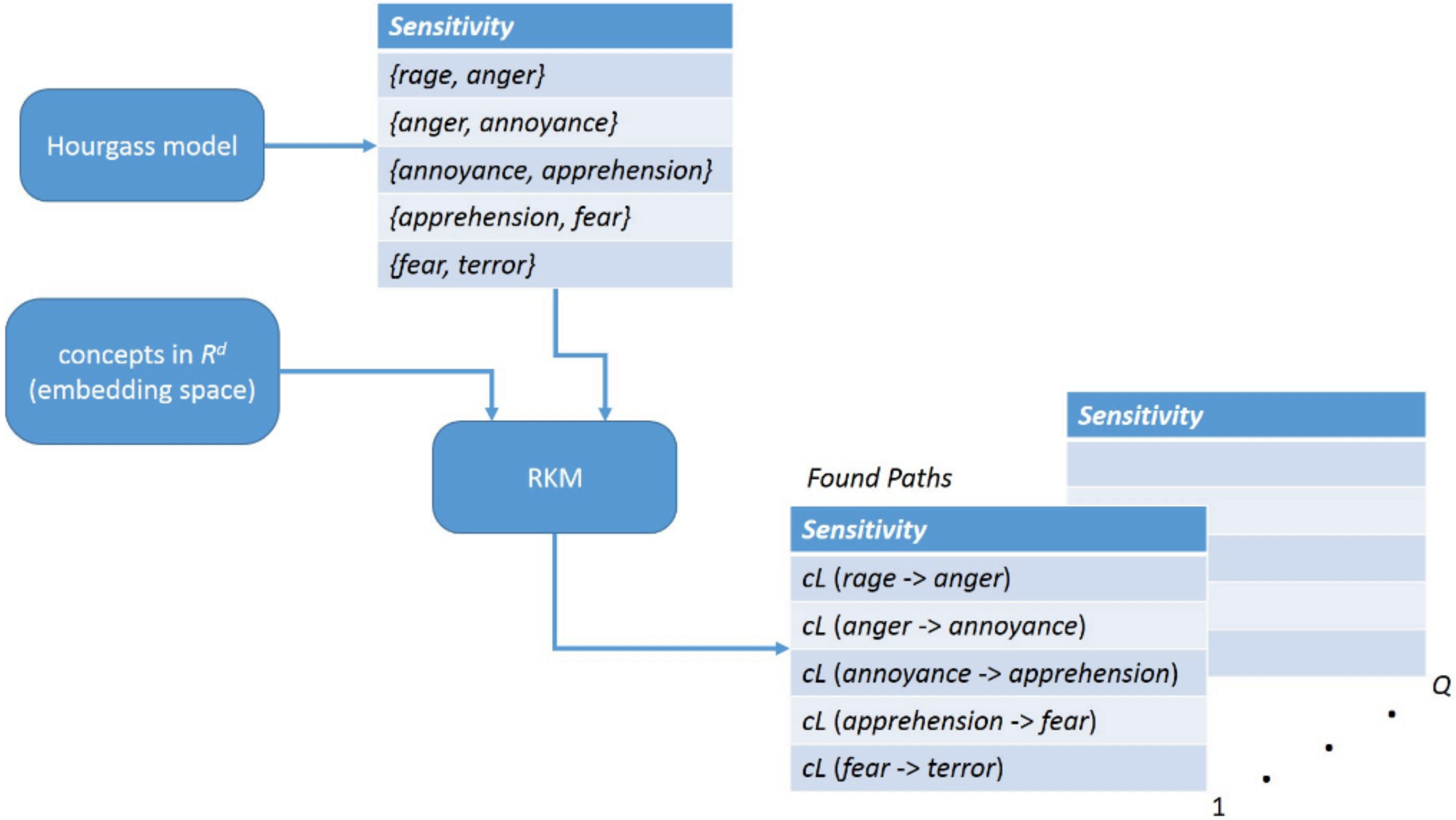
Paths in AffectiveSpace

- Procedure
  - Hourglass of emotions:
    - 4 dimensions
      - 6 landmarks concept for each dimension
  - Study data manifolds that connects landmarks concepts in Affective Space.

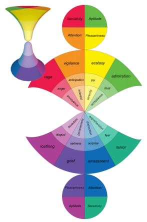
Protocol 1






Hourgass model
Sensitivity
{rage, anger}
{anger, annoyance}
{annoyance, apprehension}
{apprehension, fear}
{fear, terror}
concepts in R^d (embedding space)
RKM
Found Paths
Sensitivity
Sensitivity
cL (rage -> anger)
cL (anger -> annoyance)
cL (annoyance -> apprehension)
cL (apprehension -> fear)
cL (fear -> terror)
1
Q

Protocol 1



Hourgass model

Sensitivity
{rage, anger}
{anger, annoyance}
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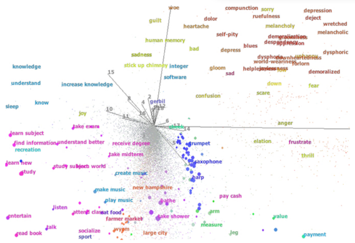
{fear, terror}



concepts in R^d (embedding space)

RKM

Found Paths

Sensitivity

Sensitivity
cL (rage -> anger)
cL (anger -> annoyance)
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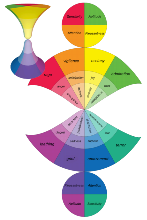
cL (apprehension -> fear)
cL (fear -> terror)

1 . . . Q

Protocol 1



Hourgass model

Sensitivity
{rage, anger}
{anger, annoyance}
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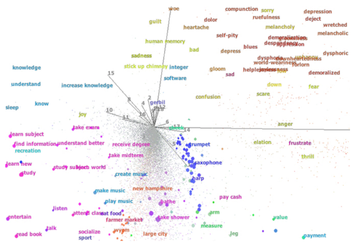
{fear, terror}



concepts in R^d
(embedding space)

RKM

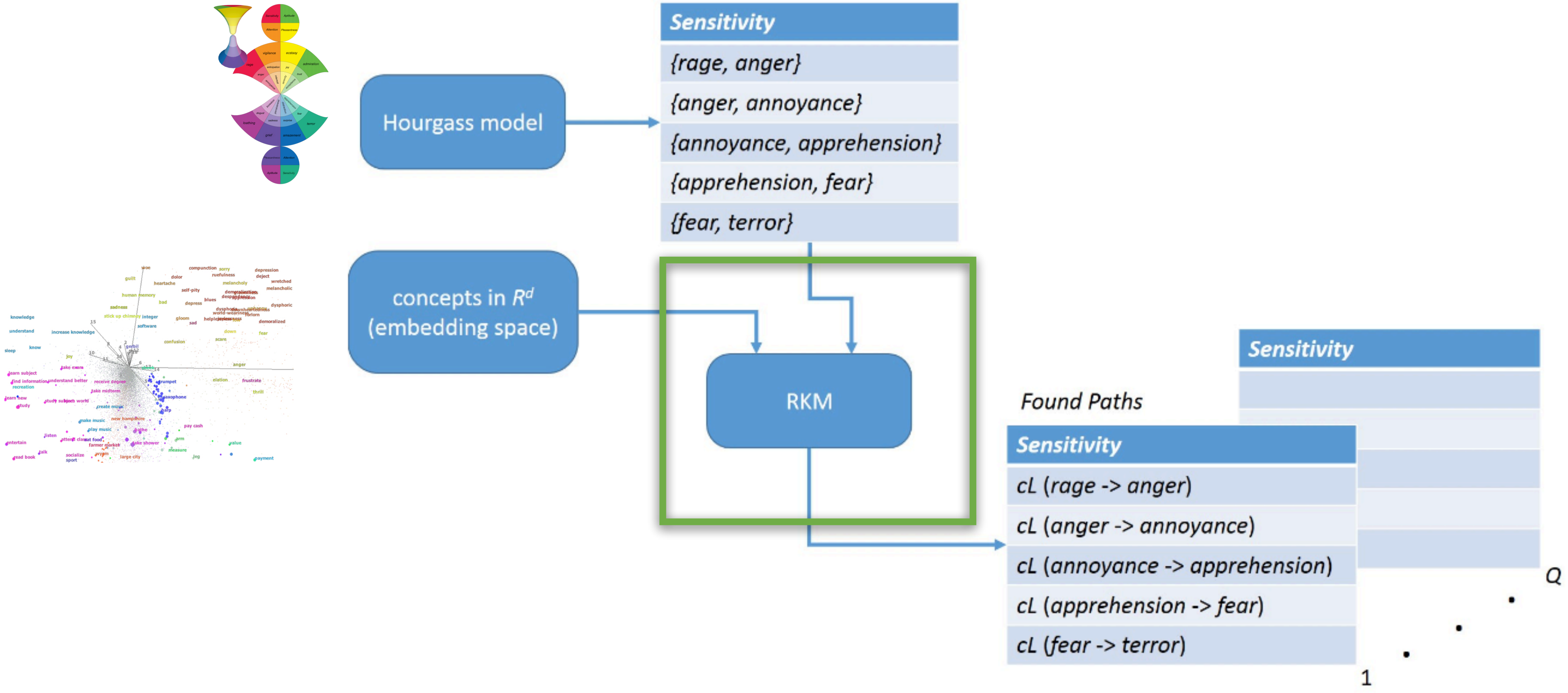
Found Paths

Sensitivity
cL (rage -> anger)
cL (anger -> annoyance)
cL (annoyance -> apprehension)
cL (apprehension -> fear)
cL (fear -> terror)

Q

1

Protocol 1



Hourgass model
Sensitivity
{rage, anger}
{anger, annoyance}
{annoyance, apprehension}
{apprehension, fear}
{fear, terror}
concepts in R^d
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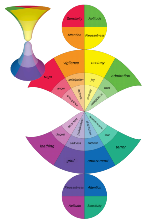
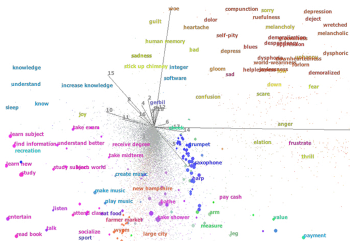
Q
1

Protocol 1





Hourgass model

Sensitivity
{rage, anger}
{anger, annoyance}
{annoyance, apprehension}
{apprehension, fear}
{fear, terror}

concepts in R^d (embedding space)

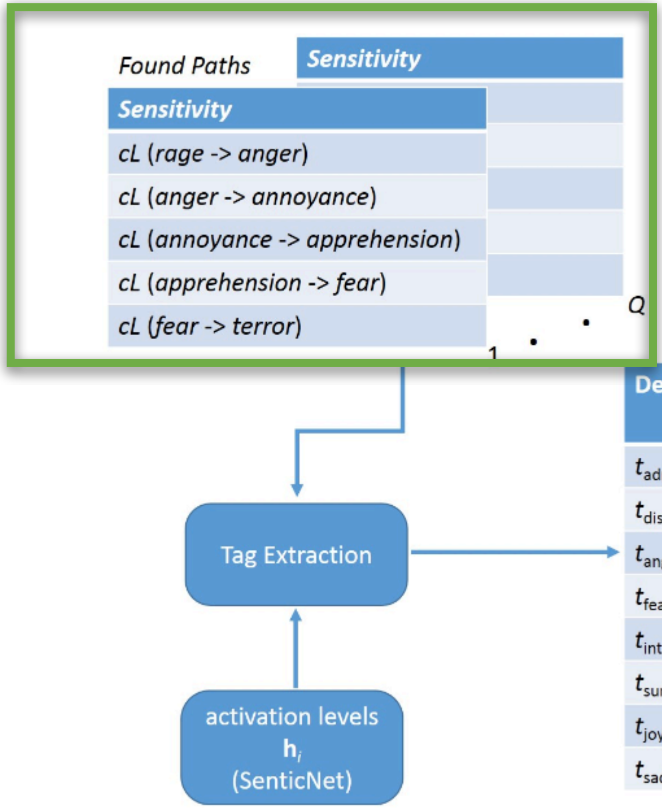
RKM

Found Paths

Sensitivity
cL (rage -> anger)
cL (anger -> annoyance)
cL (annoyance -> apprehension)
cL (apprehension -> fear)
cL (fear -> terror)

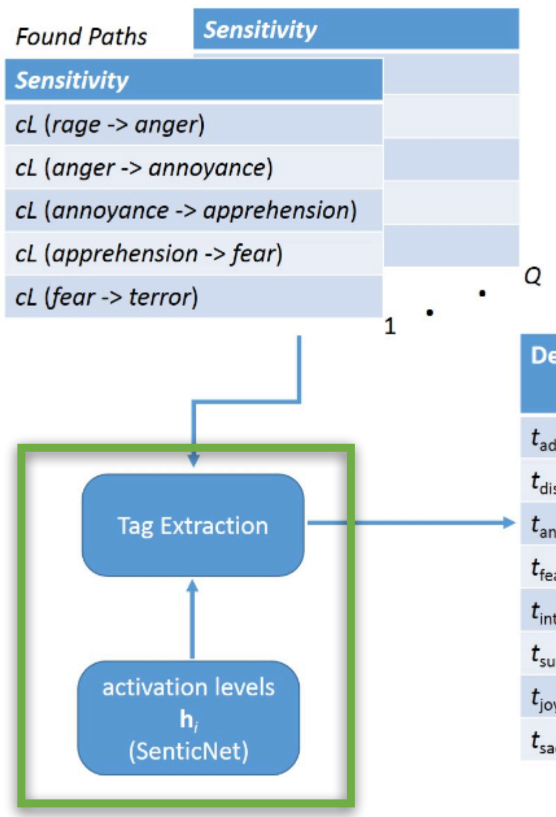
1 . . . Q

Protocol 2



Descriptors	rage -> anger	anger -> annoy.	annoy. -> apprh.	apprh. -> fear	fear -> terror
t_{adm}	...	...	...	...	...
t_{dis}	...	...	...	...	...
t_{ang}	...	...	...	...	...
t_{fear}	...	...	...	...	...
t_{int}	...	...	...	...	...
t_{sur}	...	...	...	...	...
t_{joy}	...	...	...	...	...
t_{sad}	...	...	...	...	...

Protocol 2



Descriptors	rage -> anger	anger -> annoy.	annoy. -> apprh.	apprh. -> fear	fear -> terror
t_{adm}	...	...	...	...	...
t_{dis}	...	...	...	...	...
t_{ang}	...	...	...	...	...
t_{fear}	...	...	...	...	...
t_{int}	...	...	...	...	...
t_{sur}	...	...	...	...	...
t_{joy}	...	...	...	...	...
t_{sad}	...	...	...	...	...

Protocol 2

Found Paths

Sensitivity
cL (rage -> anger)
cL (anger -> annoyance)
cL (annoyance -> apprehension)
cL (apprehension -> fear)
cL (fear -> terror)

Sensitivity

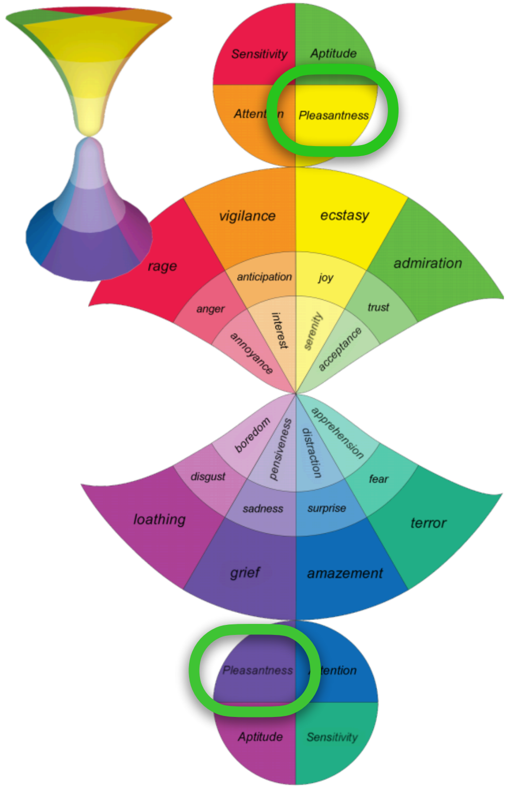
1 . . Q

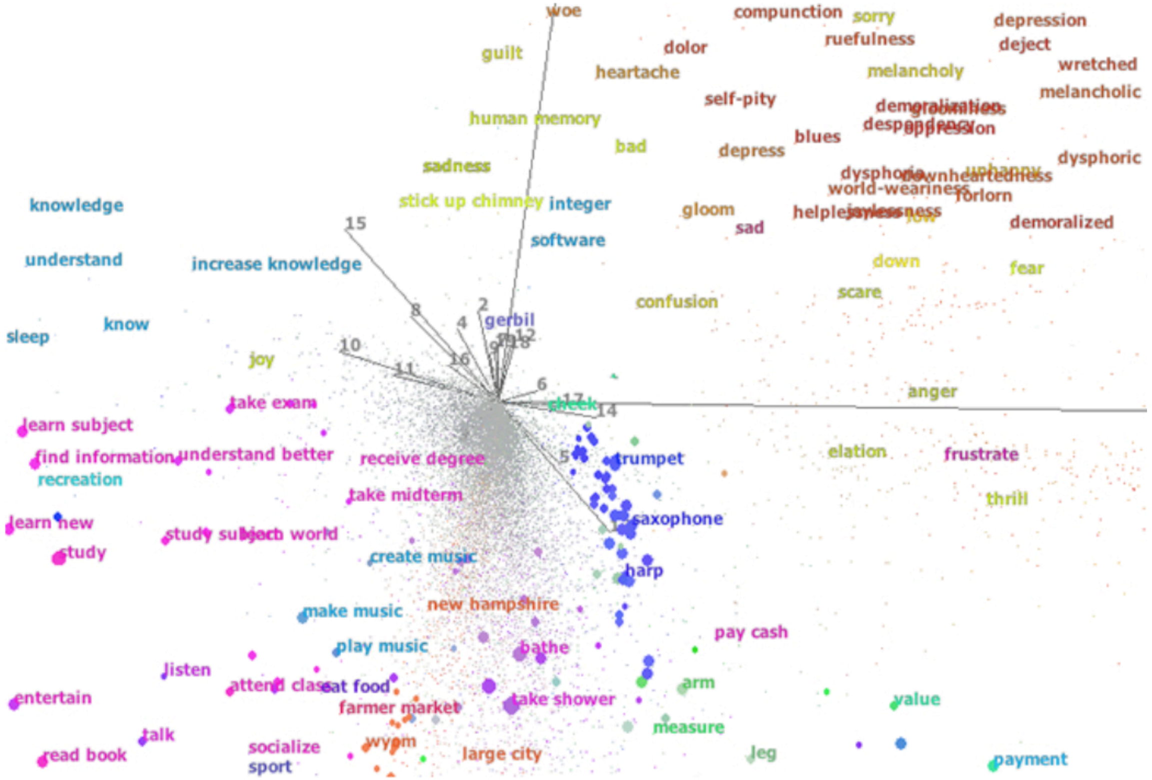
activation levels
$\mathbf{h}_i$
(SenticNet)

Tag Extraction

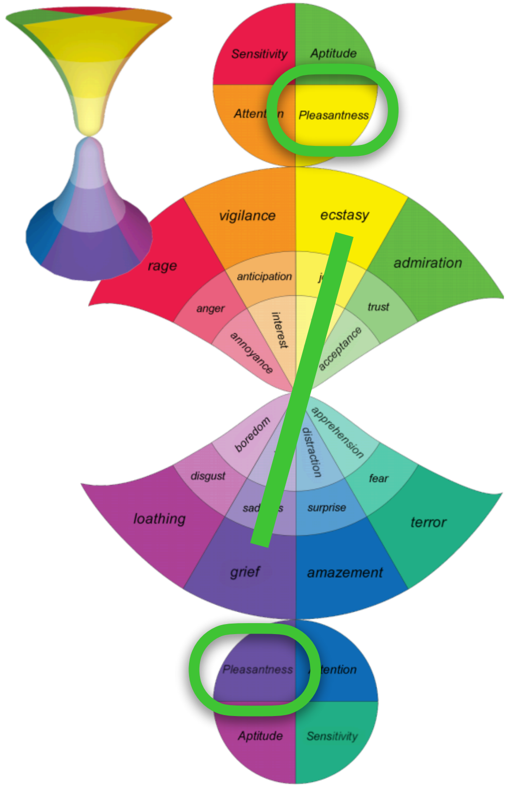
Descriptors	rage -> anger	anger -> annoy.	annoy. -> apprh.	apprh. -> fear	fear -> terror
t_{adm}	...	...	...	...	...
t_{dis}	...	...	...	...	...
t_{ang}	...	...	...	...	...
t_{fear}	...	...	...	...	...
t_{int}	...	...	...	...	...
t_{sur}	...	...	...	...	...
t_{joy}	...	...	...	...	...
t_{sad}	...	...	...	...	...

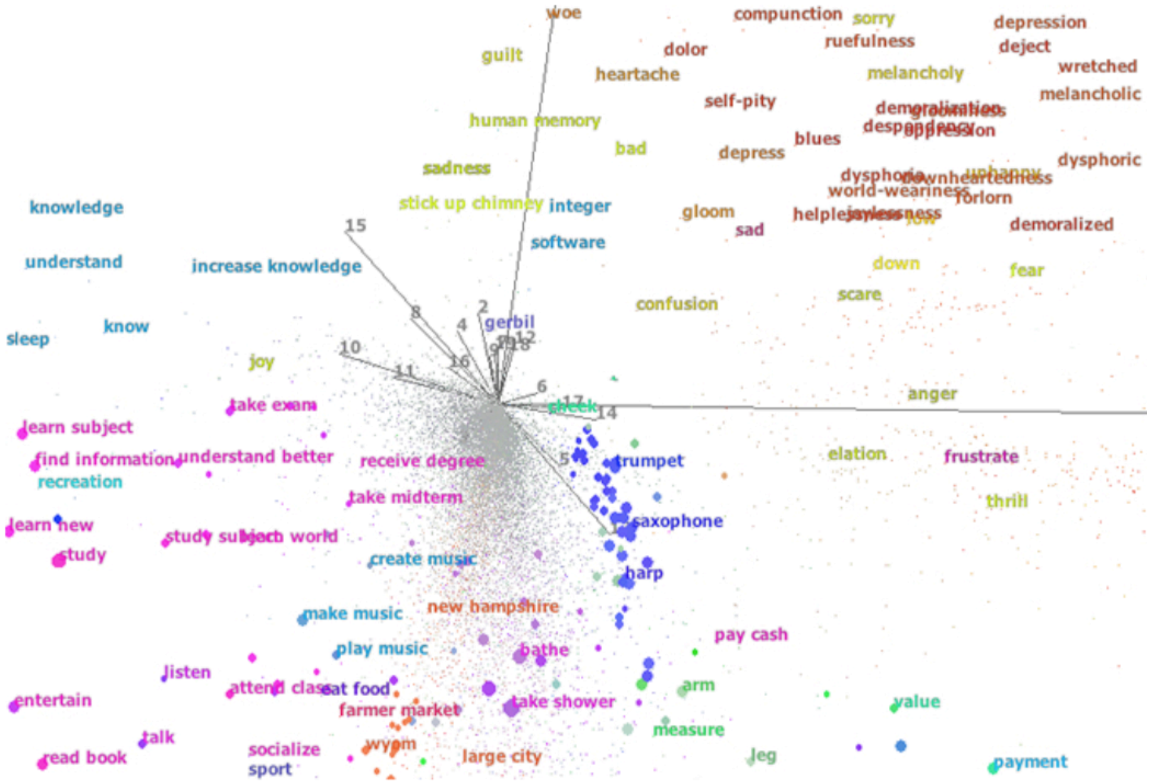
Cognitive model: The Hourglass of Emotions



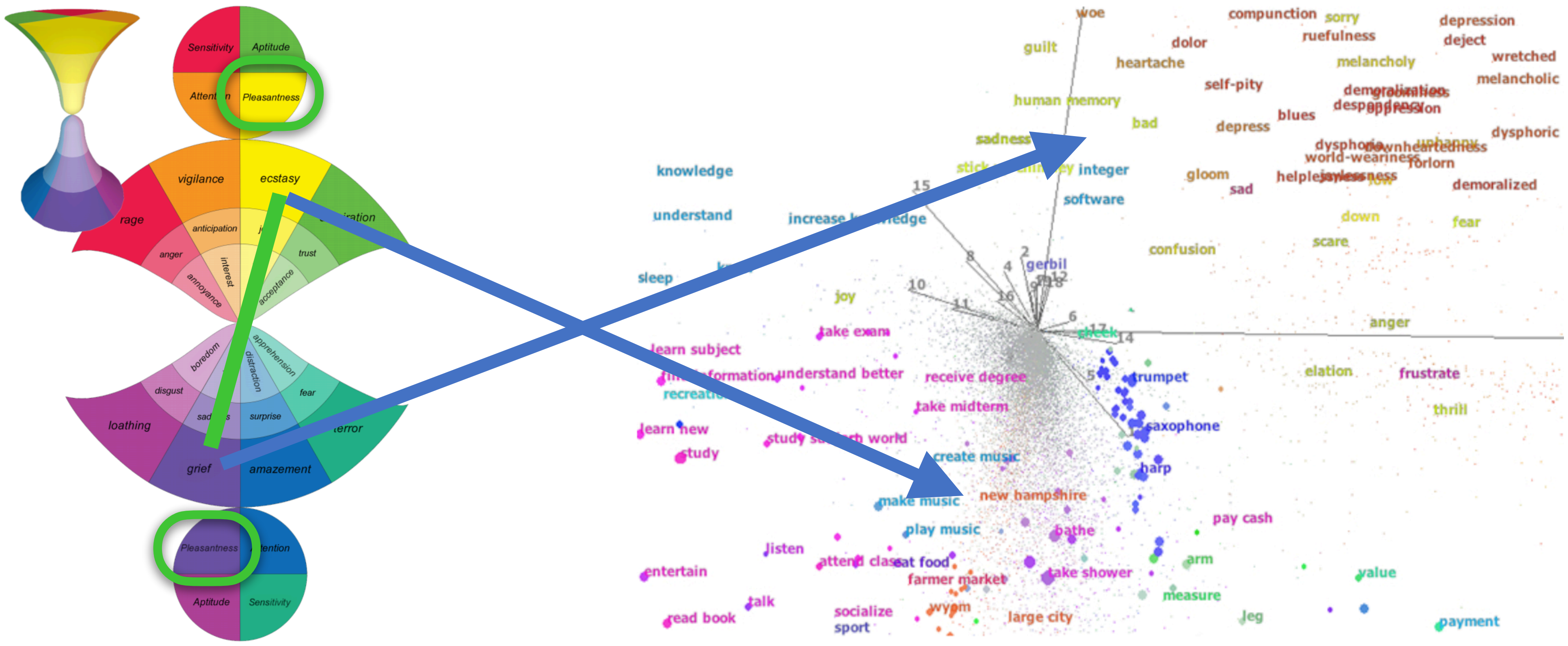


Cognitive model: The Hourglass of Emotions

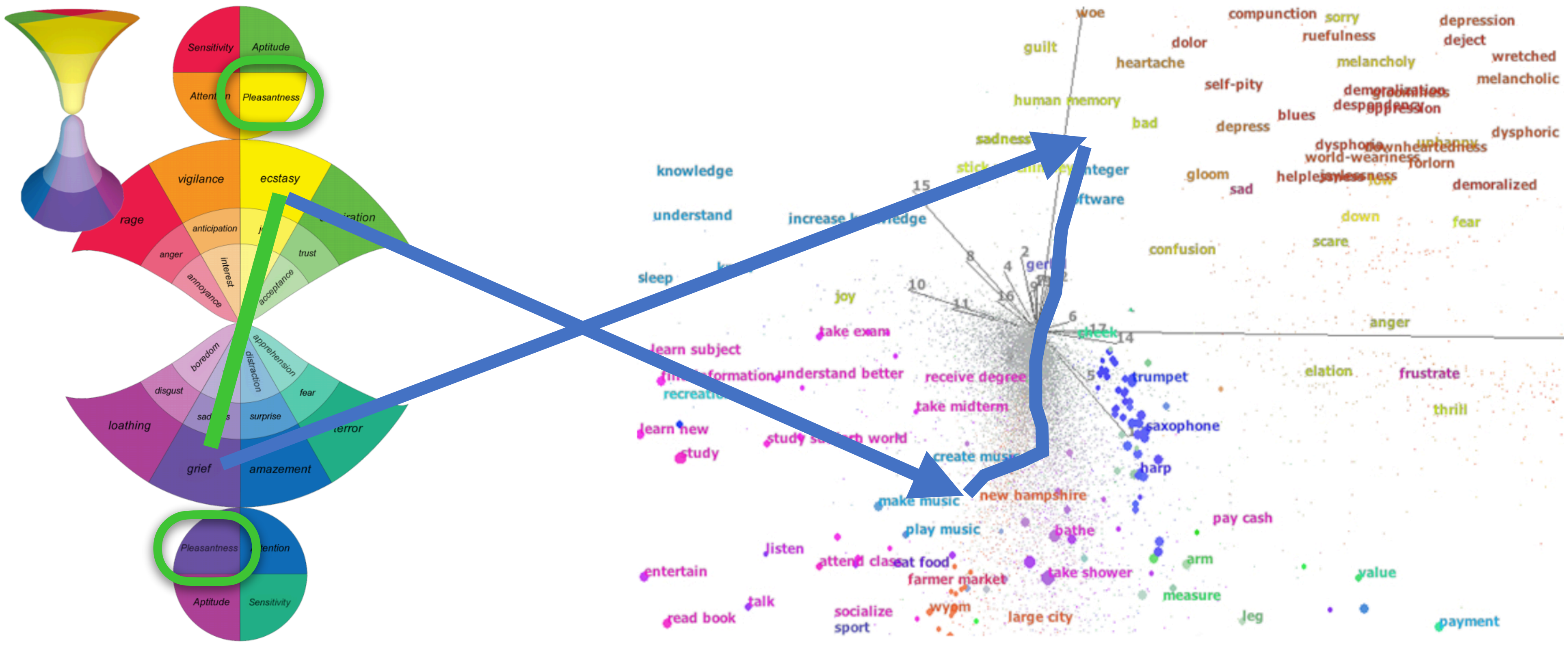




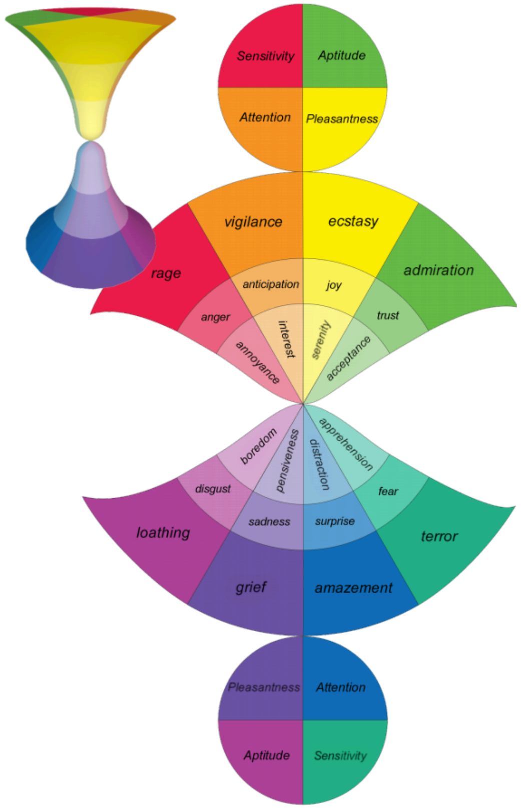
Cognitive model:
The Hourglass of Emotions



Cognitive model:
The Hourglass of Emotions



Tags



Centroids in 300 dimensions

SenticNet

Points in 4 dimensions

Sensitivity: -0.9

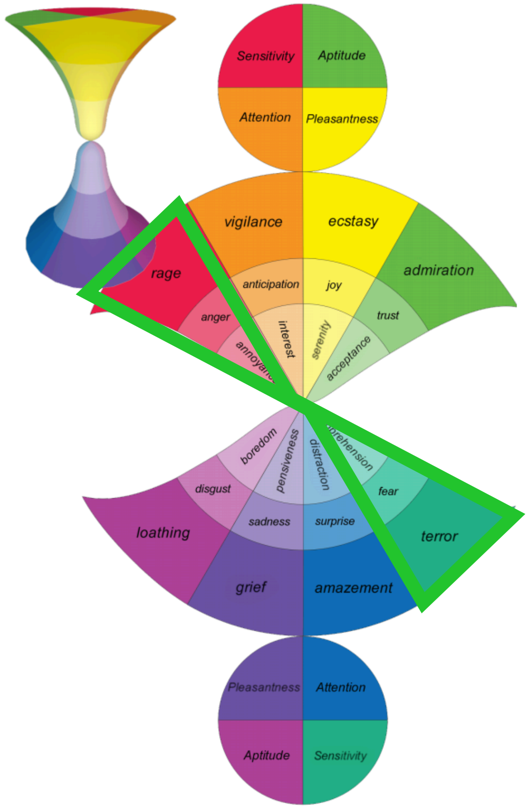
Aptitude: 0.7

Pleasantness: 0.3

Attention: -0.4

Cambria, E., Li, Y., Xing, F. Z., Poria, S., & Kwok, K. (2020). Senticnet 6: Ensemble application of symbolic and subsymbolic ai for sentiment analysis. CIKM.

Tags



Concept:

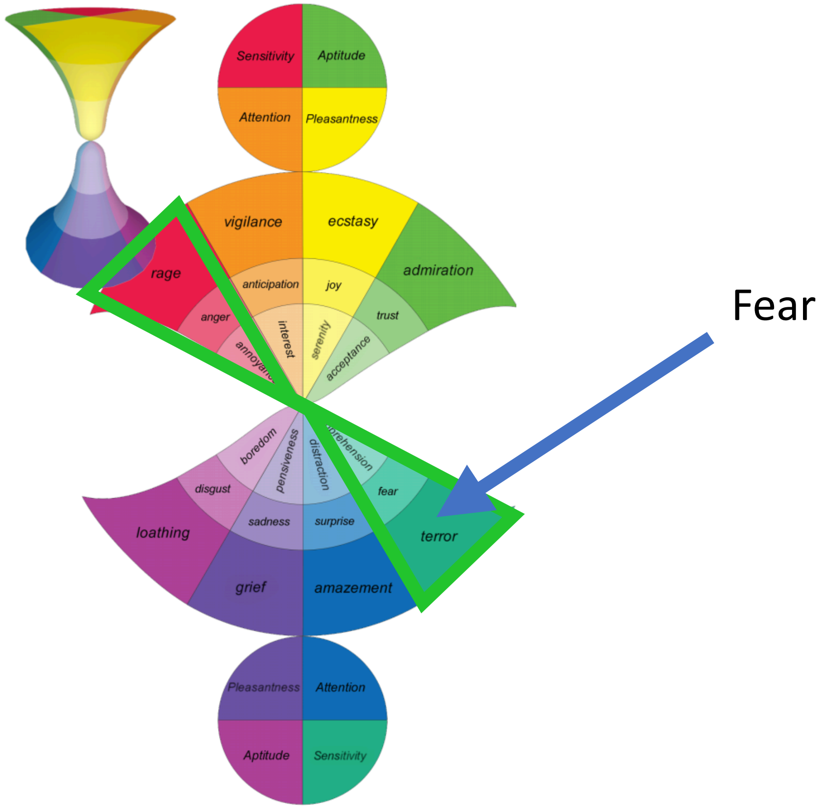
Sensitivity: -0.9

Aptitude: 0.7

Pleasantness: 0.3

Attention: -0.4

Tags



Concept:

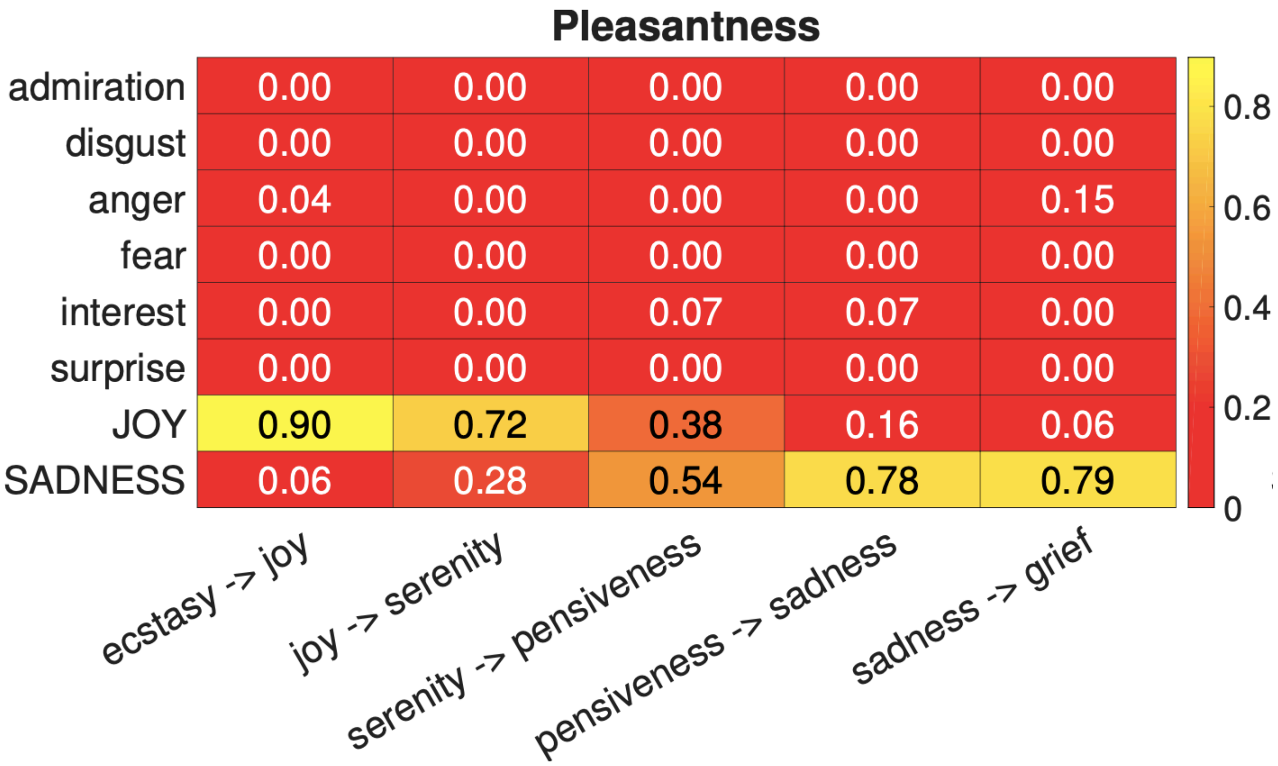
Sensitivity: -0.9

Aptitude: 0.7

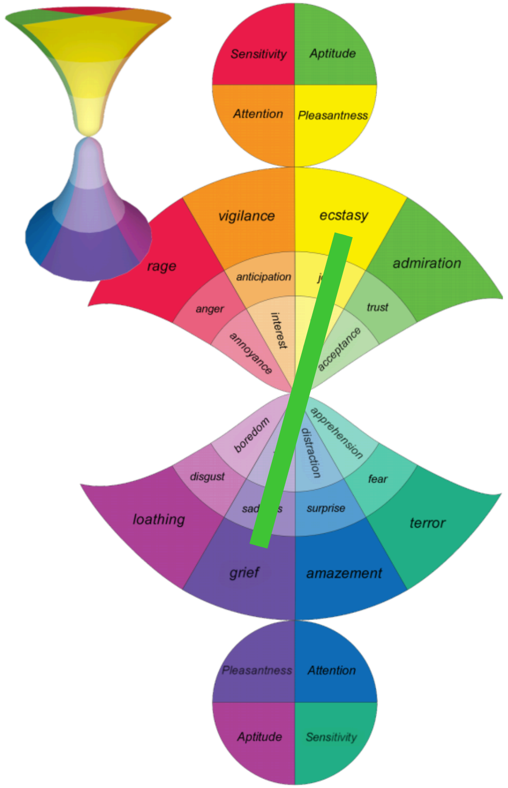
Pleasantness: 0.3

Attention: -0.4

Results


Pleasantness
admiration 0.00 0.00 0.00 0.00 0.00
disgust 0.00 0.00 0.00 0.00 0.00
anger 0.04 0.00 0.00 0.00 0.15
fear 0.00 0.00 0.00 0.00 0.00
interest 0.00 0.00 0.07 0.07 0.00
surprise 0.00 0.00 0.00 0.00 0.00
JOY 0.90 0.72 0.38 0.16 0.06
SADNESS 0.06 0.28 0.54 0.78 0.79
ecstasy -> joy
joy -> serenity
serenity -> pensiveness
pensiveness -> sadness
sadness -> grief
0.8
0.6
0.4
0.2
0

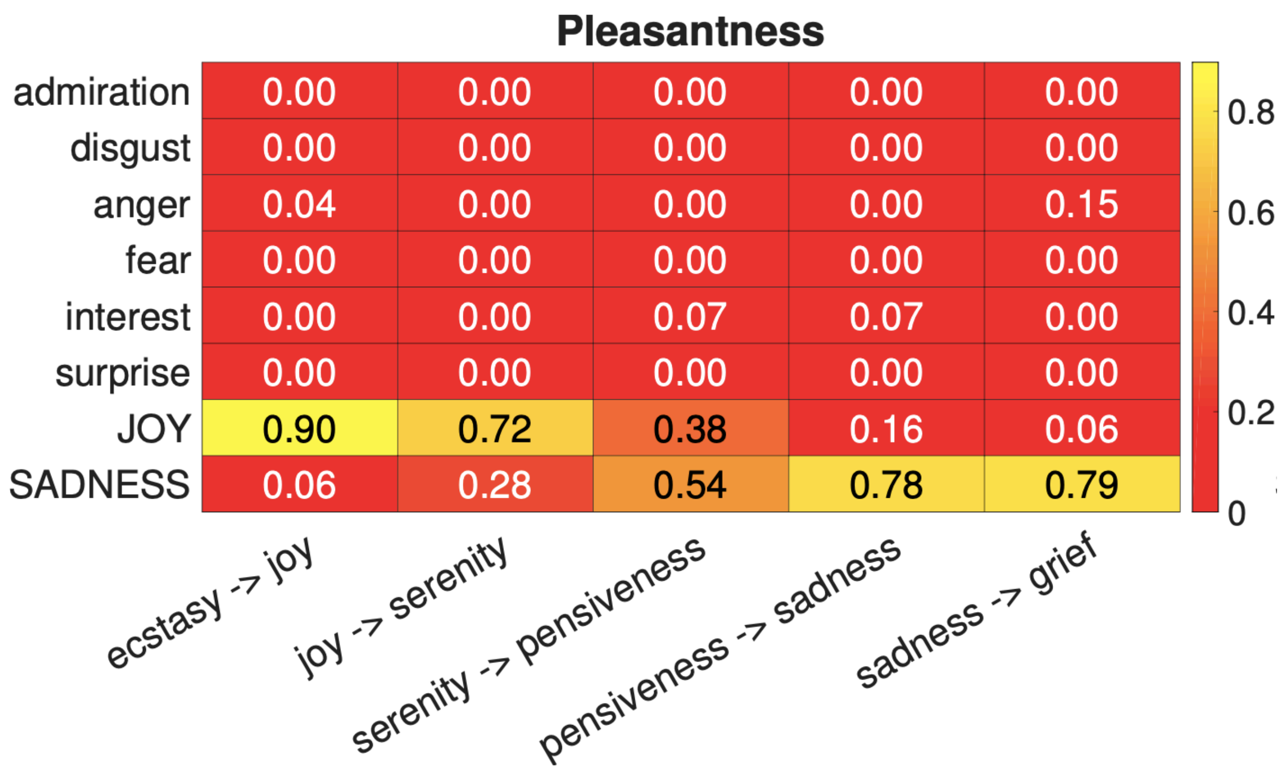
Results



Pleasantness

	ecstasy -> joy	joy -> serenity	serenity -> pensiveness	pensiveness -> sadness	sadness -> grief
ration	0.00	0.00	0.00	0.00	0.00
isgust	0.00	0.00	0.00	0.00	0.00
anger	0.04	0.00	0.00	0.00	0.15
fear	0.00	0.00	0.00	0.00	0.00
terest	0.00	0.00	0.07	0.07	0.00
rprise	0.00	0.00	0.00	0.00	0.00
JOY	0.90	0.72	0.38	0.16	0.06
NESS	0.06	0.28	0.54	0.78	0.79

Results



Pleasentness [

Conclusion

- Hardware aware solutions needs domain knowledges:
  - Good models
  - AI algorithms
  - Hardware and software resources

- Examples
  - Image polarity detection
  - Embeddings analisys

Thank you for your attention