

Automated Encoding of Motives in Psychological Picture Story Exercise

Master's Thesis Presentation

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29.08.2017

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Agenda

Introduction

Data sets

Methods

- Word embeddings

- Improving word embeddings

- Features and classifiers

Results

- Observations on tested methods

- Comparison to Baselines

Conclusion and Outlook

Introduction

Implicit motives

- have been studied since the 1950s
- influence behaviour
- are unconscious
- are typically studied regarding need for power, achievement and affiliation
- are measured using *Thematic apperception test* (TAT) or *Picture Story Exercise* (PSE)

TAT and PSE

- Test subjects are shown images
- possibly just for a couple of seconds
- are asked to write short stories about the images.



Figure 1: Examples for images in TAT and PSE from Rheinberg 2008; Schultheiss 2013

Motive Induction Studies

- Arouse a motive in one of two test subject groups, have them write stories
- analyze stories by themes, aggregate themes into coding scheme
- use scheme to blindly code stories
- if scheme is good, structural differences arise.

Why Automate This Process?

- Process is guided by intuition
- Coder training takes about 20 hours
- Study coding takes up to 40 hours

Very little research on this topic as of yet:

- Halusic using synsets and neural networks
- Ring and Pang using bag of words

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They mimic coding rather than classifying motive induction studies

Data sets

PSE/TAT Stories from several studies:

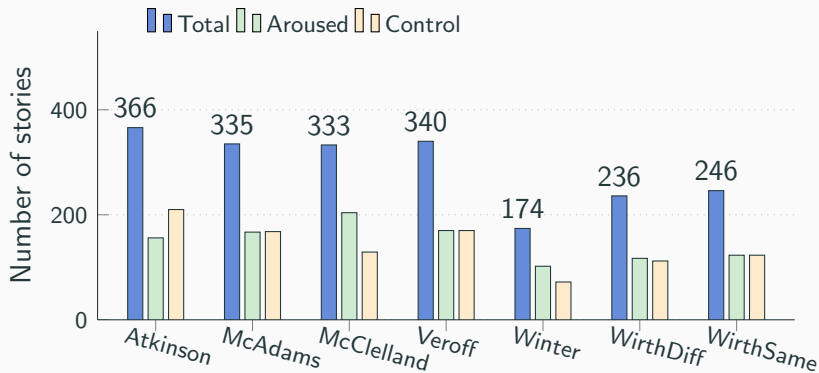


Figure 2: Number of stories per Study

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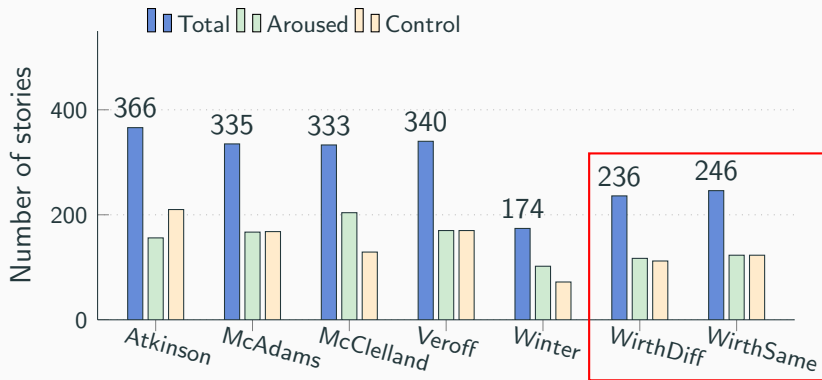


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Methods

Word embeddings

Word embeddings

- are high-dimensional vectors
- describe words semantically (e. g. sex)
- describe words syntactically (e. g. inflection)

We try word2vec and GloVe embeddings

More dimensions mean more information $\Rightarrow$ we train 400 and 600 dimensions

Word embeddings depend on word co-occurrence $\Rightarrow$ try training on corpus that is similar to classified texts

- Wikipedia
- Fan fiction

Methods

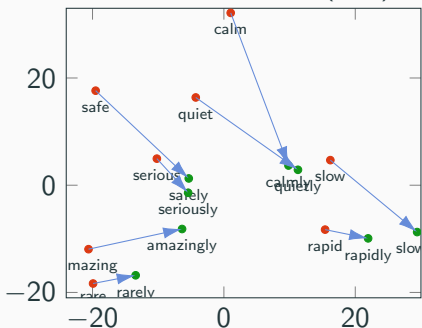
Improving word embeddings

Retrofitting

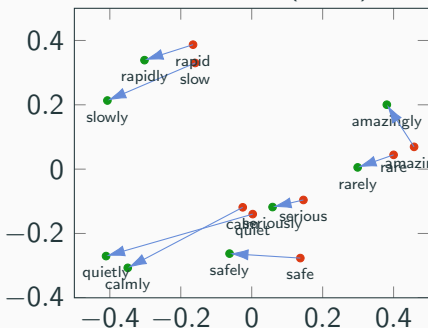
Word vectors have been retrofitted with synonym information from *WordNet* synonyms (wns) and *The paraphrase database* (ppdb).

Retrofitting

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(a) Before retrofitting



(b) After retrofitting with ppdb

Figure 3: PCA of adjective to adverb relationship of different words in the 400 dimensional word2vec embedding space trained on ffcorpus

Ultradense word embeddings

Rotating the word embedding space allows to represent one kind of semantics in one specific dimension

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We optimize on LIWC categories from Schultheiss' research:

- *nAff*: Other (“her”, “himself”, ...) Friends (“acquaintan*”, ...)
- *nPow*: Space (“above”, “beyond”, ...) Tentative (“doubt”, “uncertain*”, ...)
- *nAch*: Achievement (“perfection”, “try”, ...) Optimism (“pride”, “bold”, ...).

We employ negative sampling for the antonyms

Methods

Features and classifiers

- Term-frequency inverse-document-frequency weighting
- classified by an SVM

Centroid Vector: $\vec{d}$

Aggregate vector by summation and normalization

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Look into influence of

- norm applied
- retrofitting
- stop word removal
- image id

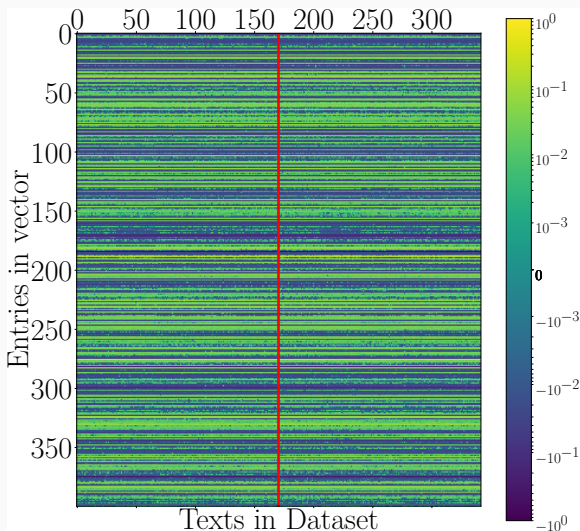


Figure 4: $\vec{d}_{l2}$ on the Veroff dataset using the 400d GloVe vectors trained on the fanfiction corpus

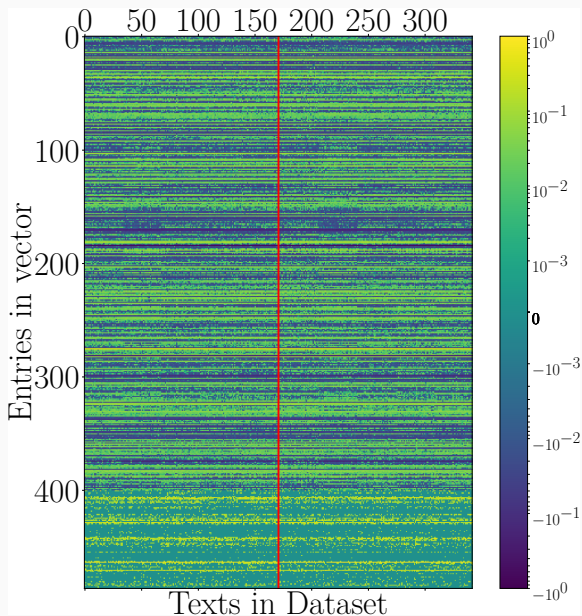


Figure 5: $\vec{d}_{l2,nostop}$ on the Veroff dataset using the 400d GloVe vectors trained on the fanfiction corpus

$\vec{d}$ is classified by an SVM and random forest

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$\vec{d}_{ultradense}$ is not classified by the SVM

$$\vec{d}_{ultradense} = \frac{\sum_{\vec{v}_i \in D} ortho(\vec{v}_i)}{norm(d)} = ortho\left(\frac{\sum_{\vec{v}_i \in D} \vec{v}_i}{norm(d)}\right).$$

Not covered due to time constraints:

- Word Mover's Distance and k -Nearest Neighbor
- Clustering word vectors
- Special weighting of vectors during summation

Results

Observations on tested methods

General observations

- no significant influence of dimensionality
- significant, but negligible influence of word embedding training corpus

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Observations regarding optimizations

- stop word removal only for GloVe embeddings beneficial
- l_2 norm sometimes beneficial
- both combined more consistently beneficial
- retrofitting generally not beneficial

- Generally perform poorer than SVM
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No clear influence of ultradense subspace.

Method cannot be used to train on one dataset and test on another

- captures mostly general theme of story
- images not consistent across studies

Results

Comparison to Baselines

Accuracy per story

	<i>Atkinson</i>	<i>McAdams</i>	<i>McClelland</i>	<i>Veroff</i>	<i>Winter</i>	<i>WirthDiff</i>	<i>WirthSame</i>
Winter	51.75% ± 4.90	50.74% ± 4.17	61.24% ± 4.59	57.35% ± 2.08	57.29% ± 3.04	N/A	N/A
Bag of Words	62.50% ± 4.30	54.75% ± 5.64	60.85% ± 6.27	63.09% ± 3.92	54.55% ± 6.1	52.5% ± 7.12	46.8% ± 5.46
$\vec{d}_{l2, nostop}$ and SVM	<u>64.73%</u> ± 4.32	<u>54.34%</u> ± 4.94	<u>61.62%</u> ± 7.5	<u>60.44%</u> ± 4.98	<u>56.95%</u> ± 4.66	<u>57.63%</u> ± 8.35	53.61% ± 5.58

Table 1: Comparison of results of different classification methods per story; gray: non significant results, $p < 0.05$

Accuracy per author

	<i>Atkinson</i>	<i>McAdams</i>	<i>McClelland</i>	<i>Veroff</i>	<i>Winter</i>	<i>WirthDiff</i>	<i>WirthSame</i>
Winter	52.33% ± 13.3	57.22% ± 6.05	67.41% ± 12.9	52.50% ± 12.5	62.50% ± 5.56	N/A	N/A
Bag of Words	70.49%	59.52%	68.47%	76.47%	58.62 %	52.54%	45.16%
$\vec{d}_{l2, nostop}$ and SVM	<u>75.41%</u>	<u>58.33%</u>	<u>68.47%</u>	<u>77.94%</u>	<u>68.97%</u>	<u>59.32%</u>	<u>61.29%</u>

Table 2: Comparison of results of different classification methods per author; gray: non significant results, $p < 0.05$

Conclusion and Outlook

- Filtering of noise from natural arousal state of participants
- Possible side channels: authorship attribution, choice of words
- Cross study validity

Current research: Classifier for stories on par with Winter Coding System (within a study)

Future research:

- Cross study classifier
- Assigning scores to stories or authors
- Possibly increase interpretability

Thank you for your attention!

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