Learning Word Embeddings for a Latin Corpus

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Pomona College

April 10, 2020

But First, a Story

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- Soon the heat starts to get to you and you find yourself in need of a drink

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- Luckily you see a local and ask them if they could point you to a drinking fountain

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- It's a nice sunny day so you've decided to spend some time at a local park
- Soon the heat starts to get to you and you find yourself in need of a drink
- Luckily you see a local and ask them if they could point you to a drinking fountain
- Their response: 'There's a bubbler just over there!'

Morales of the Story

What does that story teach us?

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Need a mathematical representation for natural language data!

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$$\texttt{embeddings} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}$$

Types of Representations

Definition

We say a vocabulary of words has been **one-hot-encoded** *if*

- *each word is represented by a vector with dimension equal to the size of the vocabulary*
- *the entries of the vectors corresponds to a specific word in the vocabulary.*
- *the* i^{th} *word in our vocabulary is represented by a vector with a value of 1 in the* i^{th} *entry and 0 in all other entries.*

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$$\texttt{we} = \begin{pmatrix} 0.98 \\ -1.45 \\ 0.22 \\ 0.06 \\ -3.78 \end{pmatrix}$$

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$$\texttt{going} = \begin{pmatrix} -0.32 \\ 0.33 \\ 2.79 \\ 0.45 \\ 0.73 \end{pmatrix}$$

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$$\texttt{create} = \begin{pmatrix} 0.41 \\ 0.60 \\ -0.42 \\ 0.55 \\ 0.78 \end{pmatrix}$$

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$$\texttt{latin} = \begin{pmatrix} 3.20 \\ 0.51 \\ -0.72 \\ 0.08 \\ 1.50 \end{pmatrix}$$

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$$\texttt{word} = \begin{pmatrix} -0.47 \\ 0.45 \\ 0.97 \\ 0.68 \\ -0.78 \end{pmatrix}$$

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$$\texttt{embeddings} = \begin{pmatrix} 6.23 \\ -0.78 \\ 0.93 \\ -0.03 \\ 0.44 \end{pmatrix}$$

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Key Difference

One-hot are sparse and large, distributed are dense and small!

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- method for creating ditributed word embeddings.

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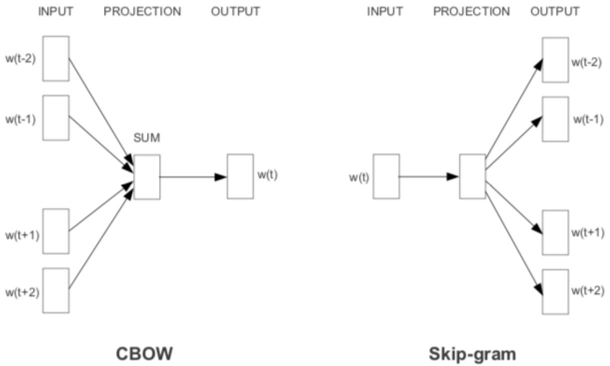
- Continuous Bag of Words (CBOW)
  - maximize the probability of predicting target words from context
- Skipgram
  - maximize the probability of predicting context words from target

Visual Intuition



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Learning using a skipgram

Given a corpus of words $w_1, w_2, \ldots, w_T$ the skipgram minimizes

$$\frac{1}{T} \sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j} | w_t) \tag{1}$$

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$$p(a|b) = \frac{\exp(v_a'^{\top} v_b)}{\sum_{w=1}^{W}\exp(v_w'^{\top} v_b)} \tag{2}$$

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where W is the size of our vocabulary and v'_w and v_w are the input and output vector representations of word w.
The weights for each word are updated using stochastic gradient descent

$$w^{t+1} = w^t + \eta_t \frac{\partial}{\partial w}\ell(w) \tag{3}$$

Training a Latin Model

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- Under-resourced and under-studied
  - few benchmarks for comparing results

My Latin Models

3 Different Data Sources

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1. word2vec
2. Fasttext (n-grams)

The Evaluation Problem

After a thorough training of your model(s) we are excited to see how 'good' our embeddings are. So, we inspect a few of them.

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```
[ 1.09798884e+00  6.61867380e-01 -7.10478052e-02  1.08630925e-01
  1.90411139e+00 -1.34148002e-01  1.13010979e+00 -1.08128226e+00
  5.67232482e-02 -1.53587058e-01 -4.61597502e-01  2.20323277e+00
 -2.83151940e-02 -1.61308491e+00 -7.17172861e-01  1.03687203e+00
  9.62423146e-01 -1.09708142e+00 -2.44244242e+00  8.22242856e-01
 -5.69651365e-01 -1.57382798e+00  1.92259073e+00  1.61573005e+00
 -1.87173045e+00 -4.40778702e-01  8.33371878e-01 -3.92222732e-01
 -5.92744529e-01  8.38984668e-01  8.04344654e-01  1.07055962e-01
 -2.29991511e-01 -6.51594162e-01 -8.89630079e-01 -1.25787973e+00
 -2.66330659e-01 -8.97910058e-01 -1.34007168e+00 -1.63498962e+00
  2.19974113e+00  3.55621070e-01  1.38610697e+00  4.99659151e-01
  1.83429384e+00  1.45139420e+00  1.27718091e+00 -5.23355544e-01
 -1.48872185e+00 -8.93208265e-01 -2.76439548e-01 -1.15471005e+00
  5.90652406e-01 -1.46208286e+00 -1.07289457e+00  2.24772835e+00
 -6.43072533e-04 -8.49872053e-01  1.41535699e-01 -1.29253221e+00
  1.33586717e+00  1.43089890e+00 -7.10735202e-01  3.68400872e-01
  3.47683936e-01  1.00279522e+00 -9.98684585e-01  9.28291202e-01
  1.26067567e+00 -1.19633090e+00 -1.00435853e+00 -6.27937138e-01
  1.02863836e+00 -1.45649803e+00 -1.00423229e+00 -1.11265707e+00
 -1.33893037e+00  8.99451971e-01  8.59849989e-01  8.97351146e-01
  1.95721543e+00 -2.38950324e+00  6.98350430e-01 -2.54332781e+00
 -7.80221343e-01  1.34824312e+00 -1.30275965e+00  4.19737220e-01
  7.49867558e-01  1.43526709e-02 -3.36812735e-01  6.33926690e-01
 -1.28516543e+00 -9.78036046e-01 -9.70386505e-01  1.48103321e+00
  1.77720714e+00 -6.30774140e-01  6.73609793e-01  1.51666775e-01]
```

```
[-0.2927009  -2.3539     -3.082364   -2.0755804  -0.23387048  0.03116352
 -3.4240723   0.6804483   2.5297556   1.4924724  -2.4403913  -0.30286705
  3.3442798  -0.45448813 -0.8306715  -0.03494536  0.31276062  1.6929202
 -3.229696   -2.8762164   3.9146178  -0.32805213  0.6030931  -0.88103676
  1.0879899  -1.7850647   2.5750897  -1.7574708  -4.274682   -0.62027305
 -1.0076166   0.8643299  -0.8952144   3.1832883   3.9998395   3.2029138
 -1.5560957   0.27520418 -0.966296    1.0861672  -0.8834181  -2.5094414
 -1.9215351   1.0475558  -2.3829036  -0.17971425 -2.8454487   4.4128757
  0.23126438 -0.58600175  2.3757505  -0.08426343  0.6372437  -2.4128644
 -1.5134279  -0.44377014 -0.18394051 -3.542668   -2.3582625   1.5922571
  0.30302525  3.3288202   0.4322284  -0.3159594   2.7113795  -4.014404
  2.4380522  -2.5136967   3.5966437   3.757738    2.2040672  -0.1174969
 -0.42089543 -2.2368116  -0.10117842  2.6468835   2.606288   -1.93117
 -2.2637906  -1.4581017   0.891239    0.47737953  0.6579282   2.549008
 -0.7854796  -5.4956417  -0.9731244  -0.50446683 -0.5956649  -1.3335679
  3.1565733  -0.6824405   1.283595    2.0075195   1.0156357   0.34581745
 -2.6737473   1.6112593   2.4512193   0.465902  ]
```

```
[ 3.4993453  -0.75153375  2.7960842   1.0670502   1.7269794   2.849036
  2.3116152   0.28173736  0.7484232   1.8855542  -0.17695513  0.75033337
  3.0245388   2.2880986   0.62054646  3.8393073   1.3523717   1.1088774
  0.4298605   0.68544114  0.05531956  0.02740468 -0.06775122  0.7071461
  0.6200045   1.6111546  -1.6065401   0.29958934  2.1255572   3.9588451
  2.2673967  -2.420242   -1.5391635   1.5550674   3.338346    2.6921241
  4.594245    1.6169097   4.448282   -3.3279974   1.5572077   1.1702842
  0.8155618  -2.965235    1.2714497  -0.23951891  3.8141346  -0.52887446
 -1.9785266  -3.3365355  -2.4357328  -0.03013381  5.2083526  -0.47481996
 -2.44593     1.2577963  -1.8394886  -0.06880338  1.7498951  -1.2576197
  1.3084195  -2.5954428  -2.5381258  -1.4663447  -1.3752079  -1.2812922
  2.5025816   2.6445158  -0.25550297 -1.6185617  -0.34789237 -0.43534958
 -0.18697618  1.2172858  -3.026618   -1.9473408  -2.2698424   1.3054887
 -2.340305    4.3331575   0.38164425 -2.977643    2.29641    -7.2448053
 -0.6058418  -1.5438882   0.6236802   6.0693827   0.98486584  1.1576533
 -0.49797067 -1.5955713  -3.2062447  -0.39012623  0.4121893   2.5176299
  2.6070173  -1.0555307   3.642642    1.1389123 ]
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[ 1.09798884e+00  6.61867380e-01 -7.10478052e-02  1.08630925e-01
  1.90411139e+00 -1.34148002e-01  1.13010979e+00 -1.08128226e+00
  5.67232482e-02 -1.53587058e-01 -4.61597502e-01  2.20323277e+00
 -2.83151940e-02 -1.61308491e+00 -7.17172861e-01  1.03687203e+00
  9.62423146e-01 -1.09708142e+00 -2.44244242e+00  8.22242856e-01
 -5.69651365e-01 -1.57382798e+00  1.92259073e+00  1.61573005e+00
 -1.87173045e+00 -4.40778702e-01  8.33371878e-01 -3.92222732e-01
 -5.92744529e-01  8.38984668e-01  8.04344654e-01  1.07055962e-01
 -2.29991511e-01 -6.51594162e-01 -8.89630079e-01 -1.25787973e+00
 -2.66330659e-01 -8.97910058e-01 -1.34007168e+00 -1.63498962e+00
  2.19974113e+00  3.55621070e-01  1.38610697e+00  4.99659151e-01
  1.83429384e+00  1.45139420e+00  1.27718091e+00 -5.23355544e-01
 -1.48872185e+00 -8.93208265e-01 -2.76439548e-01 -1.15471005e+00
  5.90652406e-01 -1.46208286e+00 -1.07289457e+00  2.24772835e+00
 -6.43072533e-04 -8.49872053e-01  1.41535699e-01 -1.29253221e+00
  1.33586717e+00  1.43089890e+00 -7.10735202e-01  3.68400872e-01
  3.47683936e-01  1.00279522e+00 -9.98684585e-01  9.28291202e-01
  1.26067567e+00 -1.19633090e+00 -1.00435853e+00 -6.27937138e-01
  1.02863836e+00 -1.45649803e+00 -1.00423229e+00 -1.11265707e+00
 -1.33893037e+00  8.99451971e-01  8.59849989e-01  8.97351146e-01
  1.95721543e+00 -2.38950324e+00  6.98350430e-01 -2.54332781e+00
 -7.80221343e-01  1.34824312e+00 -1.30275965e+00  4.19737220e-01
  7.49867558e-01  1.43526709e-02 -3.36812735e-01  6.33926690e-01
 -1.28516543e+00 -9.78036046e-01 -9.70386505e-01  1.48103321e+00
  1.77720714e+00 -6.30774140e-01  6.73609793e-01  1.51666775e-01]
```

```
[-0.2927009  -2.3539     -3.082364   -2.0755804  -0.23387048  0.03116352
 -3.4240723   0.6804483   2.5297556   1.4924724  -2.4403913  -0.30286705
  3.3442798  -0.45448813 -0.8306715  -0.03494536  0.31276062  1.6929202
 -3.229696   -2.8762164   3.9146178  -0.32805213  0.6030931  -0.88103676
  1.0879899  -1.7850647   2.5750897  -1.7574708  -4.274682   -0.62027305
 -1.0076166   0.8643299  -0.8952144   3.1832883   3.9998395   3.2029138
 -1.5560957   0.27520418 -0.966296    1.0861672  -0.8834181  -2.5094414
 -1.9215351   1.0475558  -2.3829036  -0.17971425 -2.8454487   4.4128757
  0.23126438 -0.58600175  2.3757505  -0.08426343  0.6372437  -2.4128644
 -1.5134279  -0.44377014 -0.18394051 -3.542668   -2.3582625   1.5922571
  0.30302525  3.3288202   0.4322284  -0.3159594   2.7113795  -4.014404
  2.4380522  -2.5136967   3.5966437   3.757738    2.2040672  -0.1174969
 -0.42089543 -2.2368116  -0.10117842  2.6468835   2.606288   -1.93117
 -2.2637906  -1.4581017   0.891239    0.47737953  0.6579282   2.549008
 -0.7854796  -5.4956417  -0.9731244  -0.50446683 -0.5956649  -1.3335679
  3.1565733  -0.6824405   1.283595    2.0075195   1.0156357   0.34581745
 -2.6737473   1.6112593   2.4512193   0.465902  ]
```

```
[ 3.4993453  -0.75153375  2.7960842   1.0670502   1.7269794   2.849036
  2.3116152   0.28173736  0.7484232   1.8855542  -0.17695513  0.75033337
  3.0245388   2.2880986   0.62054646  3.8393073   1.3523717   1.1088774
  0.4298605   0.68544114  0.05531956  0.02740468 -0.06775122  0.7071461
  0.6200045   1.6111546  -1.6065401   0.29958934  2.1255572   3.9588451
  2.2673967  -2.420242   -1.5391635   1.5550674   3.338346    2.6921241
  4.594245    1.6169097   4.448282   -3.3279974   1.5572077   1.1702842
  0.8155618  -2.965235    1.2714497  -0.23951891  3.8141346  -0.52887446
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```

quod erat demonstrandum

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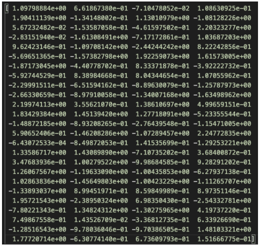

```
[ 1.09798884e+00  6.61867380e-01 -7.10478052e-02  1.08630925e-01
  1.90411139e+00 -1.34148002e-01  1.13010979e+00 -1.08128226e+00
  5.67232482e-02 -1.53587058e-01 -4.61597502e-01  2.20323277e+00
 -2.83151940e-02 -1.61308491e+00 -7.17172861e-01  1.03687203e+00
  9.62423146e-01 -1.09708142e+00 -2.44244242e+00  8.22242856e-01
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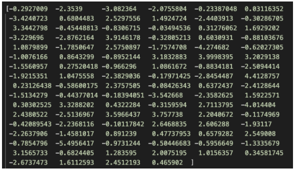

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[-0.2927009  -2.3539     -3.082364   -2.0755804  -0.23387048  0.03116352
 -3.4240723   0.6804483   2.5297556   1.4924724  -2.4403913  -0.30286705
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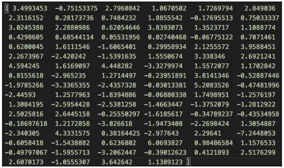

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quod   erat   demonstrandum   □

The Evaluation Problem

Problem

How to evaluate ‘goodness’?

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How to evaluate 'goodness'?

Solution

1. Use as input to some other downstream NLP task

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Desirable Attributes

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Desirable Attributes

- capture semantic similarity
- capture syntactic similarity

Odd-One-Out Evaluation

Examples

`pirum`, `pruna`, `baca`, `olea`, `denarius`

pear, **plum**, **berry**, **olive**, **denarius**

Can you pick the odd one out?

Odd-One-Out Evaluation

Examples

`consul, tribunus, praetor, magistris, episcopi`

consul, **tribune**, **praetor**, **magister**, **bishop**

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Odd-One-Out Evaluation

Examples

`homines, feminae, liberi, vir, fratres`

men, **women**, **children**, **man**, **brothers**

Can you pick the odd one out?

The Odd-One-Out Task

To play the game with our model, we do the following:

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- Check to see if chosen word is from the out-category

Top K Similarity

Another strategy: look at what's nearby

Top K Similarity

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miles	**soldier**
militio	to be a soldier
centurio	centurion
exerceo	train
legio	legion
cohors	cohort/company
militaris	military
dux	leader
cohorto	to exhort
castra	camp
hostis	enemy

Table: Top 10 most similar words

Top K Similarity

Another strategy: look at what's nearby

denarius	**coin** (1/7 oz silver)
talentum	talent
nummus	money
uncia	ounce
sestertius	coin (1/4 of a denarius)
deni	group of ten
centum	one hundred
quinquageni	fifties
viceni	twenties
centeni	hundreds
ducenti	two hundred

Table: Top 10 most similar words

Top K Evaluation

Examples

caesar

Top K Evaluation

Examples

caesar

`miles`	`antonius`	`rex`	`roma`

Top K Evaluation

Examples

caesar

miles | antonius | rex | roma

caesaris | caesarem | caesare | pompeius | antonius | pompeium

Top K Evaluation

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caesar

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`caesaris` | `caesarem` | `caesare` | `pompeius` | `antonius` | `pompeium`

Scores

Top K Evaluation

Examples

caesar

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category-in-topk accuracy $= \frac{1}{6}$

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Scores

category-in-topk accuracy $= \frac{1}{6}$

topk-in-category accuracy $= \frac{1}{4}$

Top K Evaluation

To play the top k game

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- Create a category of similar words

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To play the top k game

- Create a category of similar words
- Pick one word from the category and find the top k closest vectors

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- Calculate a score by dividing by either
    - k
    - the size of the category - 1

From Tasks to Accuracy Scores

Problem

How to test the model as a whole?

From Tasks to Accuracy Scores

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Solution

We construct a test set of words separated into categories of interest. Those categories form the basis for performing our two evaluation tasks.

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religious titles	religious figures	countries	cities
papam	ambrosius	hispania	roma
archiepiscopus	augustini	gallia	mediolanum
episcopus	gregorius	italia	byzantium
apostolus	aquinas	germania	carthago
presbyter	hieronymus	graecia	troiae
propheta	eusebius	syria	NA

Table: A portion of my test set

Scores of Interest from my Models

Accuracies for k = 3

- Christian

Scores of Interest from my Models

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  - odd-one-out = .815

Scores of Interest from my Models
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Scores of Interest from my Models

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    - topk-in-category = .036
    - Category-in-topk = .053

Scores of Interest from my Models

Accuracies for k = 3

- Christian
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- Medieval

Scores of Interest from my Models

Accuracies for k = 3

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  - Category-in-topk = .053
- Medieval
  - odd-one-out = .722

Scores of Interest from my Models

Accuracies for k = 3

- Christian
  - odd-one-out = .815
  - topk-in-category = .036
  - Category-in-topk = .053
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  - odd-one-out = .722
  - topk-in-category = .019

Scores of Interest from my Models

Accuracies for k = 3

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  - odd-one-out = .815
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- Medieval
  - odd-one-out = .722
  - topk-in-category = .019
  - category-in-topk = .029

Scores of Interest from my Models

Accuracies for k = 3

- Christian
  - odd-one-out = .815
  - topk-in-category = .036
  - Category-in-topk = .053
- Medieval
  - odd-one-out = .722
  - topk-in-category = .019
  - category-in-topk = .029
- Full

Scores of Interest from my Models

Accuracies for k = 3

- Christian
  - odd-one-out = .815
  - topk-in-category = .036
  - Category-in-topk = .053
- Medieval
  - odd-one-out = .722
  - topk-in-category = .019
  - category-in-topk = .029
- Full
  - odd-one-out = .825

Scores of Interest from my Models

Accuracies for k = 3

- Christian
  - odd-one-out = .815
  - topk-in-category = .036
  - Category-in-topk = .053
- Medieval
  - odd-one-out = .722
  - topk-in-category = .019
  - category-in-topk = .029
- Full
  - odd-one-out = .825
  - topk-in-category = .052

Scores of Interest from my Models

Accuracies for k = 3

- Christian
  - odd-one-out = .815
  - topk-in-category = .036
  - Category-in-topk = .053
- Medieval
  - odd-one-out = .722
  - topk-in-category = .019
  - category-in-topk = .029
- Full
  - odd-one-out = .825
  - topk-in-category = .052
  - category-in-topk = .075

This is the End

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