Comparing vector-based and ACT-R memory models of tag retrieval

User-customized tag prediction on Twitter and StackOverflow

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Motivation for Task

- Social-media sites are composed almost entirely of human-generated content
- There’s a lot of it (over 400M Twitter tweets created per day)
- Users are searching for information that is happening now (real-time search)
- Instead of actively searching, they are subscribing to information streams
  - Followers (Twitter), friends (Facebook), tags (StackOverflow)
- To support a user of these sites, how can we quickly and effectively connect users to the streams of content that they care about?

General Approach

- Try to figure out a user's goals on the site
  - what information concepts/sources/locations/etc. are they interested in?
- Easier for social-media sites compared to traditional search
  - Social-media sites have each user's past behavior
- Users also choose "tags" when creating content
- Seems plausible that these user-chosen tags contain important information concerning the goals of each user on a site
- So if we can predict the chosen tags, then we can better predict the goals.
  - If we can better predict a user's goals, we can recommend to them new information streams that they are interested in
- Frame the task of choosing a tag as a memory retrieval problem
  - Explore, modify, and evaluate how accurately two state-of-the-art declarative-memory retrieval theories can predict the correct tags

Motivation for Cognitive Modeling

- Recently possible to evaluate psychological theories of declarative memory on large-scale real-world tasks
  - Theories can be tested on hundreds of millions to billions of data points
  - Now possible due to:
    - Growth of social media and user-created content
    - Improved APIs and methods for extracting information
    - Improved data mining software and faster hardware

- These information-rich large-scale environments provide unique opportunities for research in declarative memory:
  - Can stress test and explore the impacts of the psychological constraints of each theory on a much larger scale than has previously been possible
  - Rapidly test and evaluate different architectural constraints and their impact on retrieval accuracy
  - Finally test the declarative memory equations on a scale that is closer to the magnitude of chunks that are stored in human memory

Research Questions

- What kinds of cognitively-plausible models can predict user-chosen tags on social media sites?
  - Look at StackOverflow and Twitter
- Compare two state-of-the-art declarative memory retrieval models
  - ACT-R's Bayesian model and a vector-based model
- Can strengths from one model be incorporated into the other?
  - Word-order from vector-based models
  - Prior likelihood and user customization from Bayesian models
- How accurate is each model in predicting the correct tags? Is one particular memory model better than the other in prediction? What about computational efficiency and scale?
- Output: Two improved and task-agnostic user-customized tag-prediction models

Example: StackOverflow

stackoverflow | Questions | Tags | Users | Badges | Unanswered

Why this is undefined behavior?

13

My answer to this question was this function:

```
inline bool divisible15(unsigned int x)
{
    //286331153 = (2^32 - 1) / 15
    //4008636143 = (2^32) - 286331153
    return x * 4008636143 <= 286331153;
}
```

It perfectly worked on my machine with VS2008 compiler, however here it doesn't work at all.

Does anyone has an idea, why it I get different results on different compilers? `unsigned` overflow isn't undefined behavior.

Important note: after some test it was confirmed it is faster than taking the remainder of the division by 15.

c++ c undefined-behavior

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edited 13 mins ago
H2CO3
93.4k •11 •59 •127

asked 54 mins ago
user2623967
2,033 •5 •29

3 Is this faster than `(x % 15) == 0`? – asveikau 50 mins ago

1 It doesn't show as undefined behavior to me? It probably integer overflows though. – PherricOxide 50 mins ago

@asveikau depends on compiler optimizations – user2623967 50 mins ago

1 Does `x * 4008636143` fit inside an int? – andre 49 mins ago

3 @millimoose Well... these are *unsigned* ints. The overflow behavior is specified. – Mysticial 44 mins ago

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Example: Twitter

Oprah Winfrey @Oprah 29 Aug
RT @BishopJakes: Getting ready for #Lifeclass with @oprah. Tweet me if you're in the house! pic.twitter.com/XQMu1W9kw5
View photo

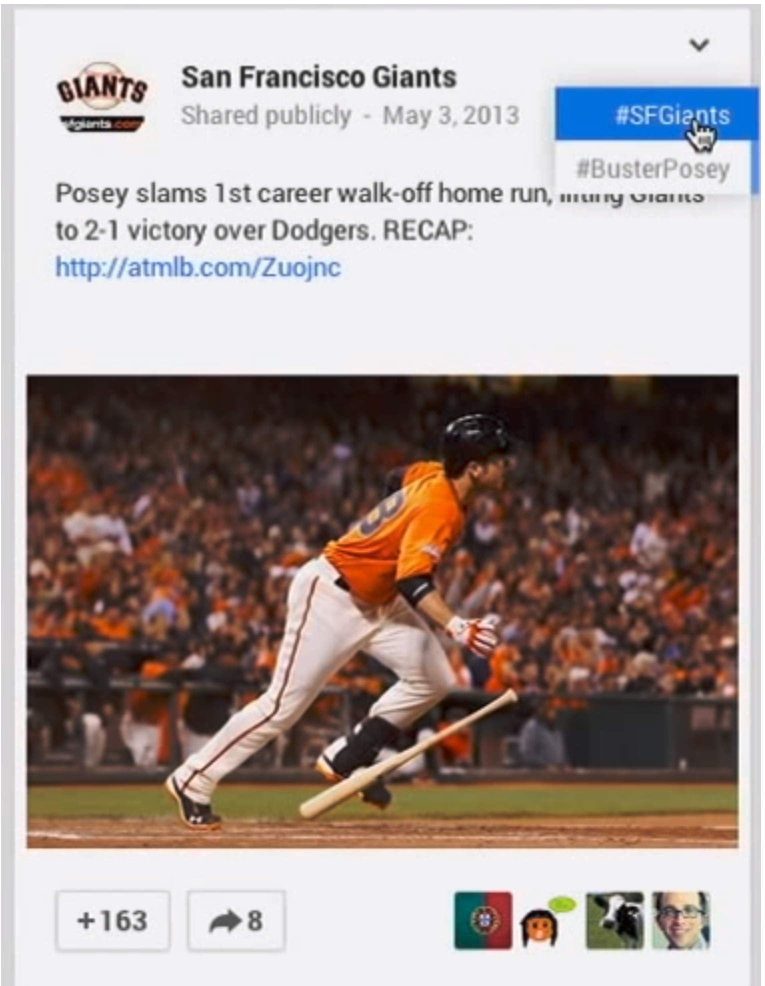
Barack Obama @BarackObama 6 Sep
Protection against employment discrimination is a no-brainer. Show your support for #ENDA today: OFA.BO/6rkVHF
Collapse Reply Retweet Favorite More

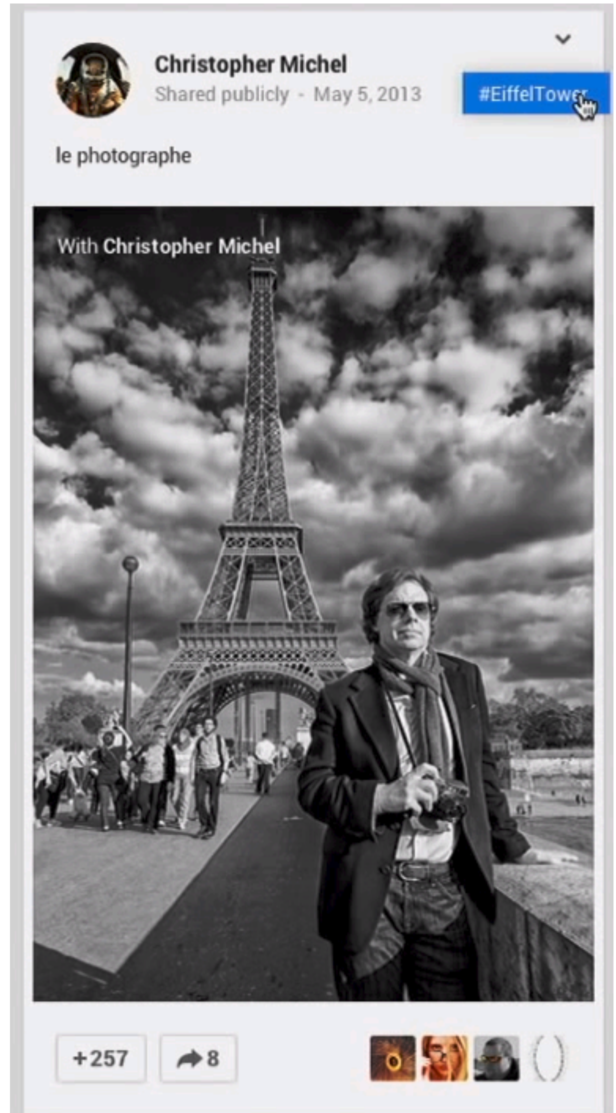
688 RETWEETS	384 FAVORITES

3:06 PM - 6 Sep 13 · Details

Teen Vogue @TeenVogue 20h
It'll take a lot to top last year's Superbowl halftime show extravaganza, but if anyone can do it, @BrunoMars can: teenv.ge/17Si69C
Expand

Example Application: Google+





Models: ACT-R Bayesian DM Model

- Naturally incorporates user prior tag use, frequency and recency effects
  - But not word order (yet)

Common Name	Equation
Activation	$A_i = B_i + \sum_{j \in c} W_j S_{ji}$
Attentional Weight	$W_j = \frac{W}{n}$
Base Level	$B_i = log \sum_{j=1}^{n} t_j{}^{-d}$
Constant Base Level	$B_i = log \frac{p(i)}{p(\bar{i})}$
Strength of Association	$S_{ji} = log \frac{p(i\|j)}{p(i\|\bar{j})} \approx log \frac{p(i\|j)}{p(i)}$
Recall Probability	$P_i = \left(1 + e^{\frac{\tau - A_i}{s}}\right)^{-1}$

Random-Permutation Vector Model

- Compressed representation of full co-occurrence matrix used for Bayesian models
  - Simplified activation calculation
  - Should scale much better
  - Can also naturally incorporate word-order information
  - ~~Might achieve better predictions?~~

Common Name	Equation
Activation	$A_i = r(m_C, m_i)$
Memory Vector	$m_i = \sum_{i \in allpast} c_i + \sum_{i \in allpast} \sum_{l \in locations} o_{i,l}$
Unordered Context	$c_i = e_i$
Ordered Context	$o_{i,l} = e_{i-l}$
Context Memory Vector	$m_C = \sum_{i \in C} c_i + \sum_{i \in C} \sum_{l \in locations} o_{i,l}$
Environment Vector	$e_i = rand$

Methods: Datasets

- Newest StackOverflow
  - Entire dataset is available, so use entire dataset. No need to extract subsets when evaluating models on StackOverflow
  - ~5M posts, ~1B co-occurrence observations

- Twitter
  - Entire dataset is not publicly available. Must extract subsets
  - Popular-users subset
    - As a starting point, current top ~2,000 users
    - Evaluate and develop model of prior likelihood of a tag that is customized to the user's past history
  - Popular-hashtags subset
    - As a starting point, current top ~500 hashtags
    - Evaluate each model's performance on a hashtag-prediction task

Methods: Experiment 1

- Analyze how a user's tag history influences chosen hashtags

- Use StackOverflow and Twitter popular-users dataset
  - Do not use popular-hashtags dataset since this set does not contain enough information about each user's history

- Test results against ACT-R decay rate equations
  - Regression to find best-fitting decay rate parameter
    - Parameter might be specific to each user

Methods: Experiment 2

- How can a user's past tagging history be incorporated into the random permutations vector-based model?
- Use StackOverflow and Twitter popular-users datasets
- Explore modifications to vector-based model to incorporate a user's tag history

Methods: Prior for Vector Models

- One approach to incorporate the user's past tagging history:
- Vector-based models produce a distribution of correlations
  - Chooses the tag with the highest correlation
- Use the distribution of correlations to compute a probability for each correlation | distribution
- Use that probability in the Hick-Hyman law to compute a log odds that a tag with that correlation is the correct tag
- Then add that log odds value to the log odds that the tag is correct | past user history (i.e., ACT-R's base-level activation term)

Methods: Experiment 3

- How can word-order information be incorporated into the ACT-R Bayesian model?

- Use Twitter popular-hashtag dataset
  - Cannot use StackOverflow dataset since tags always occur at the very end of the post

- Explore ways that incorporating word order into the Bayesian model improves tagging accuracy

Methods: Word Order for Bayesian

- One approach to incorporate word order into Bayesian co-occurrence models:

- Add an additional dimension in the co-occurrence matrix for word position

- Compute probability of a tag | context *and* word order

- Most likely will require smoothing and computational shortcuts to make this practical
  - Possibly bin and store three separate co-occurrence matrices, for words that appear “close”, “mid”, and “far” from hashtags
  - Possibly use a model with a few parameters that describes the distribution of a word’s positions relative to a hashtag
    - + Achieves a form of smoothing
    - + Still might need to memoize the co-occurrence matrices generated with this technique (i.e., one matrix for each word position relative to the hashtag

Methods: Experiment 4

- Predict tags based purely on context (i.e., no prior user history), using all datasets
- Results will show performance differences for the contextual component of each model

Methods: Experiment 5

- Test the full models (prior and context) on the StackOverflow and Twitter popular-users dataset.

- Will directly compare performance differences between the two full models, after the strengths of each model have been incorporated into the other

Conclusions: End Results

- Better understanding of how a user's past tagging history influences future tag use
- More thorough evaluation of the strengths/weaknesses of two cognitively-plausible memory models
- Improvements to each memory model where strengths of each are incorporated into the other
- Two efficient implementations of the models

Conclusions: Broader Impacts

- Produces implementations of two task-agnostic memory models that have numerous potential real-world applications
  - e.g., hashtag use on Facebook, flagging Wikipedia articles for content issues or overly-opinionated material, auto labeling incoming mail, spam filtering
- Explores how well each memory model scales to datasets with billions of co-occurrence observations
- Explores and tests architectural modifications to the memory models
- If model accuracy improves for these tasks, these modifications may improve accuracy more generally in other memory tasks
- Increases our understanding of how imposing specific architectural constraints on memory models influences what information is retrieved