
# TM-OKC: An Unsupervised Topic Model for Text in Online Knowledge Communities

Dongcheng Zhang
Emory University

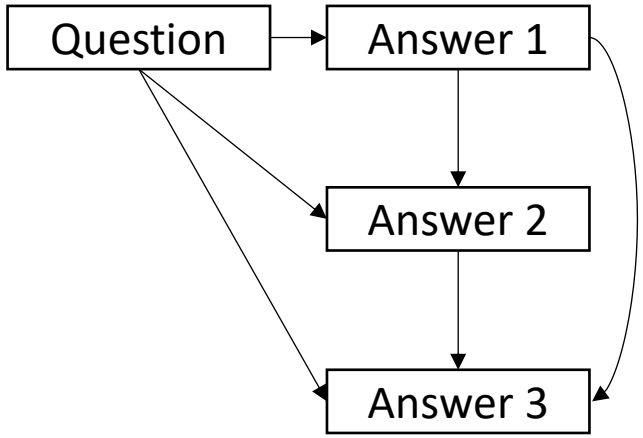
Kunpeng Zhang (KZ)
University of Maryland

David A. Schweidel
Emory University

October 14, 2023

# 1 Research motivation

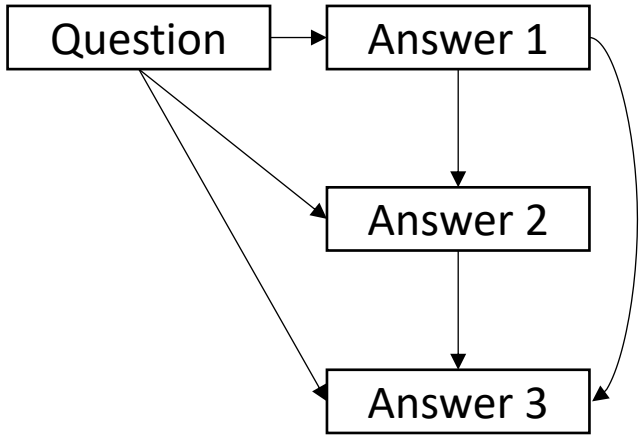
- **“Question-answer” textual data**




Note: “Question-answer” refers to a general structure

# 1 Research motivation

- **“Question-answer” textual data**




Note: “Question-answer” refers to a general structure

## Marketing analytics texts

Asked 8 years ago  Modified 4 years, 5 months ago  Viewed 93 times

1

Can you recommend a comprehensive textbook or a monograph on marketing analytics?

I'm interested in metrics, measures and statistical methods used in the field. For instance, what are the approaches at companies like Amazon and Walmart?

UPDATE: I'm looking for a text like Greene, Econometric Analysis. Econometrics is a set of statistical methods applied to economics. So, I want the same but for Marketing. I'm not interested in technology aspects, because that's the same everywhere: big data databases etc.

references  marketing

Share  Cite  Improve this question  Edited Feb 26, 2019 at 19:12

Follow

community wiki
3 revs, 2 users 100%
Aksakal

What is your quantitative background? Generally speaking, I think that it would be useful to learn regression, time series analysis, and other statistical methods. Marketing Analytics = Statistics + SQL programming + business insights – mmmmmmmmm Aug 2, 2015 at 1:33

@cwh_UCF, my background is econometrics + theor physics + programming – Aksakal Aug 2, 2015 at 1:41

Add a comment

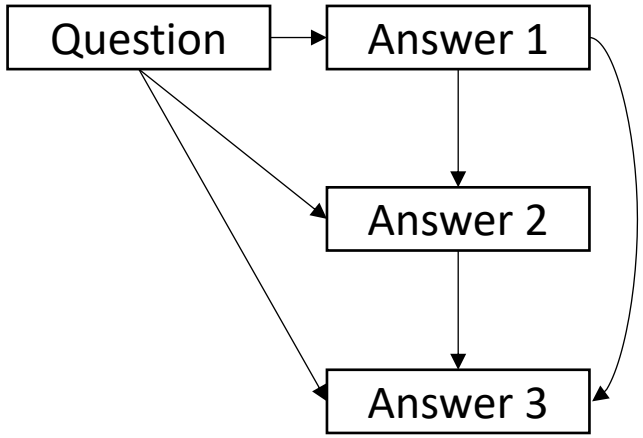
Q&A in online knowledge communities

2 Answers  Sorted by: Highest score (default)

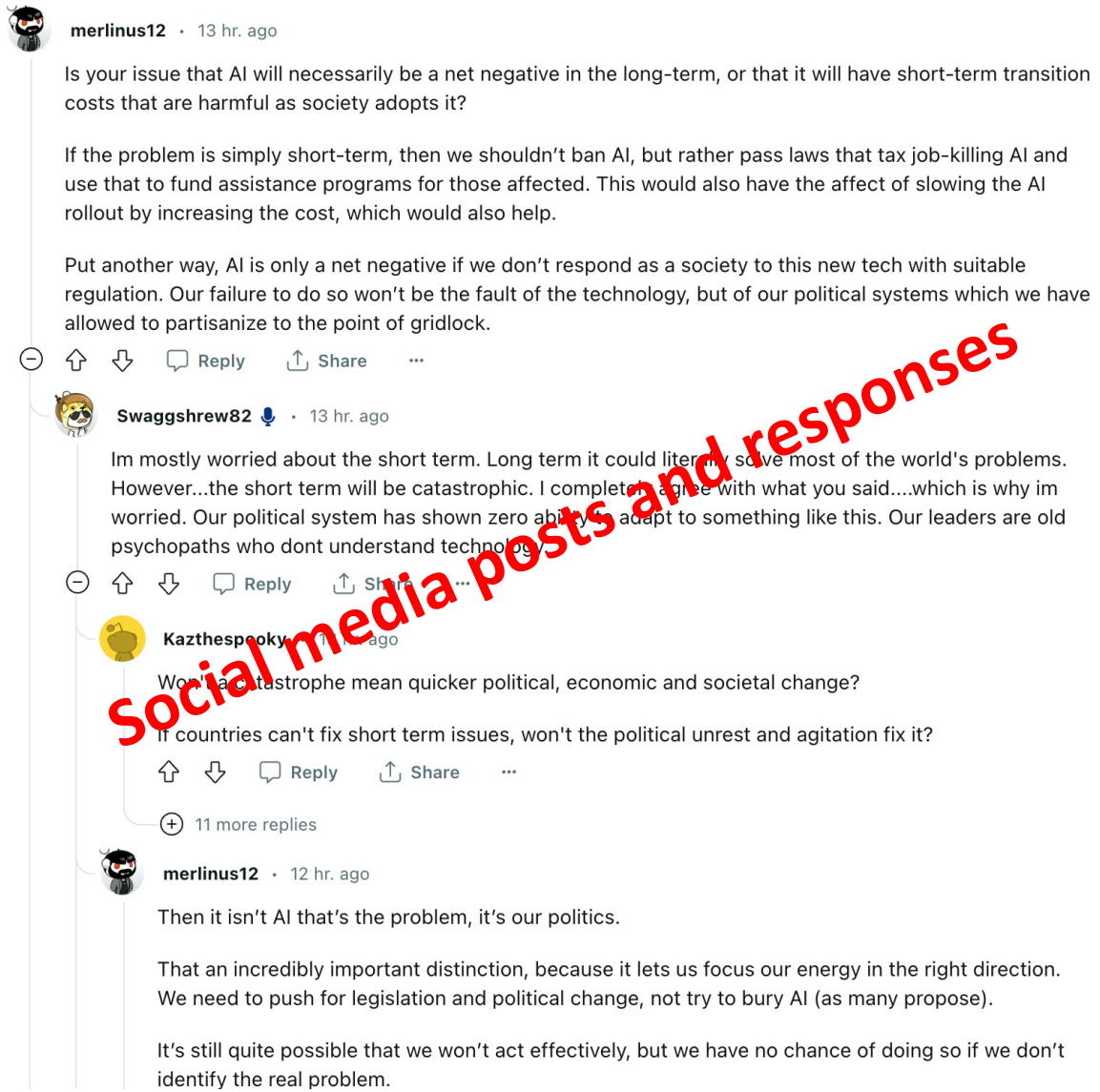
With your background, I would recommend that you learn statistics and SQL programming. For the statistics, learn linear regression, logistic regression, time series analysis, decision trees,

# 1 Research motivation

- **“Question-answer” textual data**



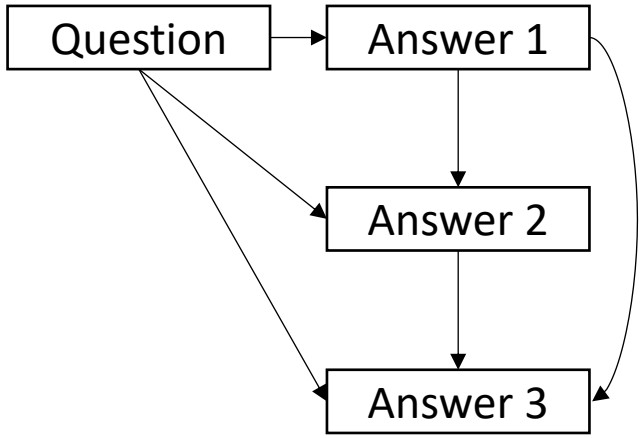

Note: “Question-answer” refers to a general structure




**Social media posts and responses**

# 1 Research motivation

- **“Question-answer” textual data**

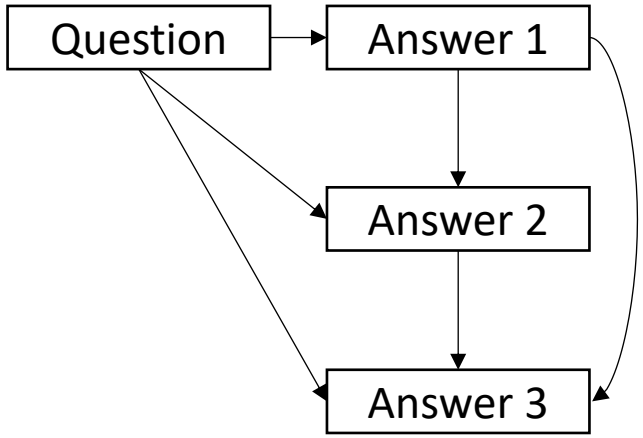



Note: “Question-answer” refers to a general structure

- **Millions of users**
  - Stack Exchange (100+M users), Quora (300+M users)
  - Twitter (300+M users), Reddit (400+M users)
- **Huge business opportunities**
  - **$ 65.31 billion** on social advertising (US) (eMarketer, 2022)

# 1 Research motivation

- **“Question-answer” textual data**




Note: “Question-answer” refers to a general structure

Gabby Tess

★★★★★ **The Dream Team of Laundry: Tide Pods with Downy Unleash the Magic!**

Reviewed in the United States on June 16, 2023

Unit Count: 73.0 | Verified Purchase

Prepare to witness the ultimate laundry alchemy with Tide Pods infused with Downy. It's like a symphony of cleanliness and freshness that will leave you in awe. Brace yourself for a laundry experience like no other!

These little wonders are the secret to transforming your laundry routine into a magical affair. With the power of Tide's cleaning prowess and the irresistible scent of Downy, your clothes emerge from the wash with a newfound brilliance and a touch of heavenly softness.

The convenience of these Tide Pods is simply unrivaled. Just toss one in, and let the enchantment begin. No measuring, no mess—just pure laundry bliss. The pods dissolve effortlessly, releasing their extraordinary cleaning powers that obliterate stains and leave your garments looking as good as new.

But wait, there's more! The infusion of Downy fabric softener takes your laundry game to the next level. Say goodbye to rough fabrics and hello to a realm of luxurious softness. Your clothes will caress your skin

Read more

2 people found this helpful

Helpful | Report

Pearl Chri an

★★★★★ **Last 3 orders have pods that have ruptured**

eviewed in the United States on July 15, 2023

Unit Count: 61.0 | Verified Purchase

The last 3 orders have had pods that were ruptured and then they leak to other pods and stick together. I have a new container that I have not used yet. What cane be done about this? Usually 4 or 5 pods stick together and you cannot get them apart without them bursting. So I am losing 4 or 5 pods per container.

Helpful | Report

Gabby Bon

★★★★★ **Works!**

Reviewed in the United States on July 28, 2023

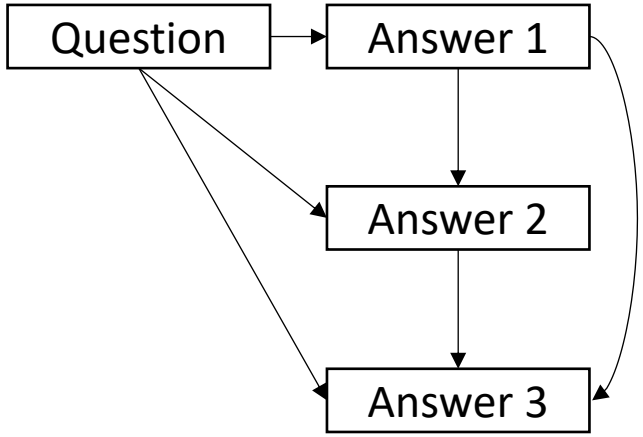
Unit Count: 61.0 | Verified Purchase

Have always used Tide. Our clothes are clean and fresh. Use to use the liquid Tide and now have totally switched to the pods- so convenient!

**Product descriptions and reviews**

# 1 Research motivation

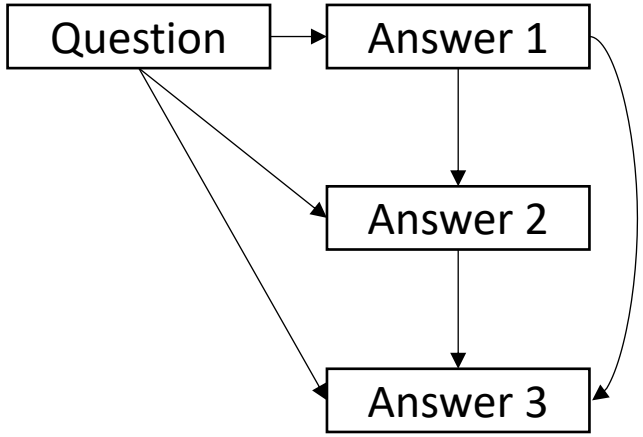
- **“Question-answer” textual data**




Note: “Question-answer” refers to a general structure

# 1 Research motivation

- **“Question-answer” textual data**




Note: “Question-answer” refers to a general structure

**How to extract information from texts?**

- **User interests’ discovery**
- **Consumer behavior analysis**
- **Empirical IS research**

# 1 Research motivation

- **Topic models**

Document → "Summarize" → **Interpretable topics**

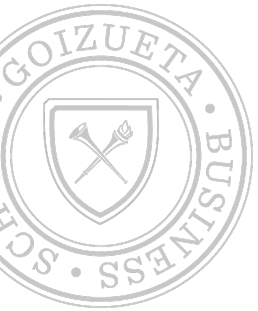
Example: … my recent Starbucks experience … delightful taste … rich, velvety caramel perfectly complemented the smooth espresso … nuanced flavors … incredible service … genuine warmth and enthusiasm … passion for coffee … attention to detail … every step executed with precision … danced on my taste buds … memorable journey … marriage of taste and service.

↓ Topic modeling

Topic 1 (42%): service

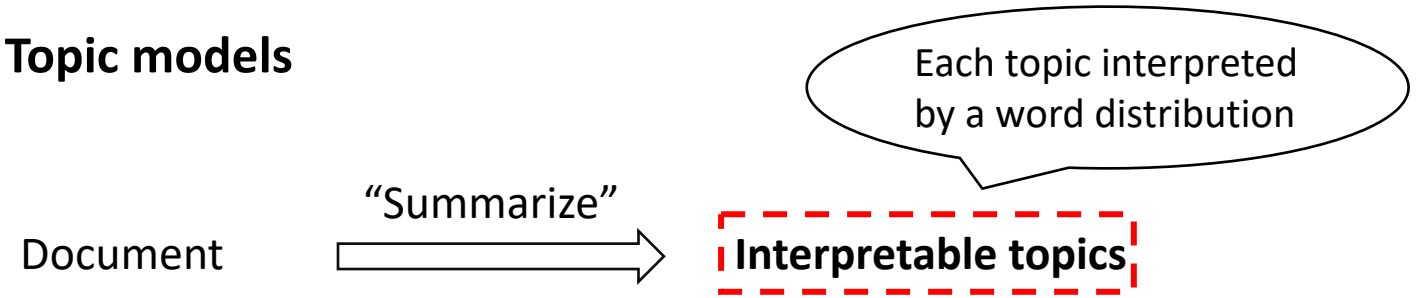
Topic 2 (29%): taste

Other topics … … …



# 1 Research motivation

- **Topic models**




Example: … my recent Starbucks experience … delightful taste … rich, velvety caramel perfectly complemented the smooth espresso … nuanced flavors … incredible service … genuine warmth and enthusiasm … passion for coffee … attention to detail … every step executed with precision … danced on my taste buds … memorable journey … marriage of taste and service.

Topic modeling

| Topic 1 (42%): service | |
|---|---|
| Service | 0.069 |
| Experience | 0.041 |
| Journey | 0.039 |
| Warmth | 0.029 |
| Enthusiasm | 0.018 |

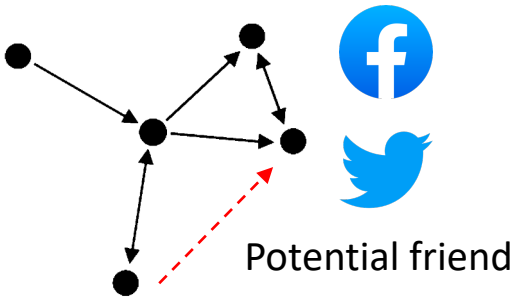
| Topic 2 (29%): taste | |
|---|---|
| Taste | 0.180 |
| Flavor | 0.049 |
| Smooth | 0.042 |
| Rich | 0.033 |
| Nuance | 0.027 |

Other topics … … …

# 1 Research motivation

- **Topic models**

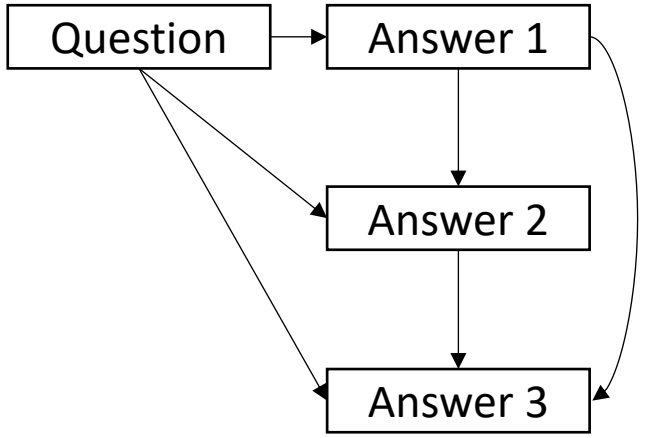
Document → "Summarize" → **Interpretable topics** → **Downstream applications**

| User profiling | Friendship suggestion | … … … | Trending topic detection |
|---|---|---|---|
| User interests' discovery<br><br>User A: football fan<br>User B: foodie<br>… … |  <br> | | Analyzing customer reviews<br><br>• CRM<br>• Brand perception<br>• Product design |
| (Geva et al. 2019, *MIS Quarterly*) | (Li et al. 2016, *Management Science*) | | (Büschken and Allenby 2020, *Marketing Science*) |

# 1 Research motivation

- **Topic models**
  - Existing generic topic models (e.g., LDA)
    - Posts are independent
    - No structural relationships

**Observed structure**




Question: … data I am working with is not 100% clean … What are the best practices in such a case as this?

Answer A: 1. Do not modify the original data. Having the original data source intact is important ...

Answer B: … I agree with the other posters that you should not modify the original data, but add fields for corrected values. I developed a technique in our systems (opengeocode.org) …

**Goal: Develop a new topic model to capture the complex structural relations**

# 2 Model development: Key features

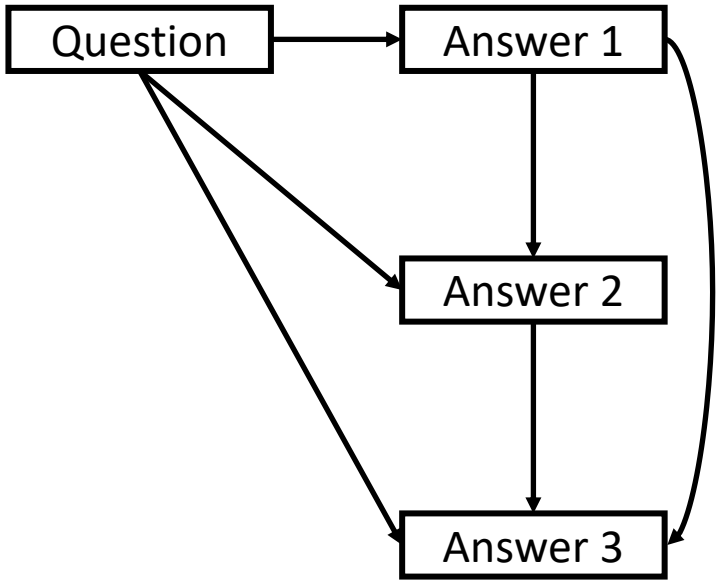
- **Three key features**

**(1) Q&A relationship**

Dependency
Q ⟶ A

+

Variation
Q ≠ A




**(2) Threaded structure + heterogeneity**

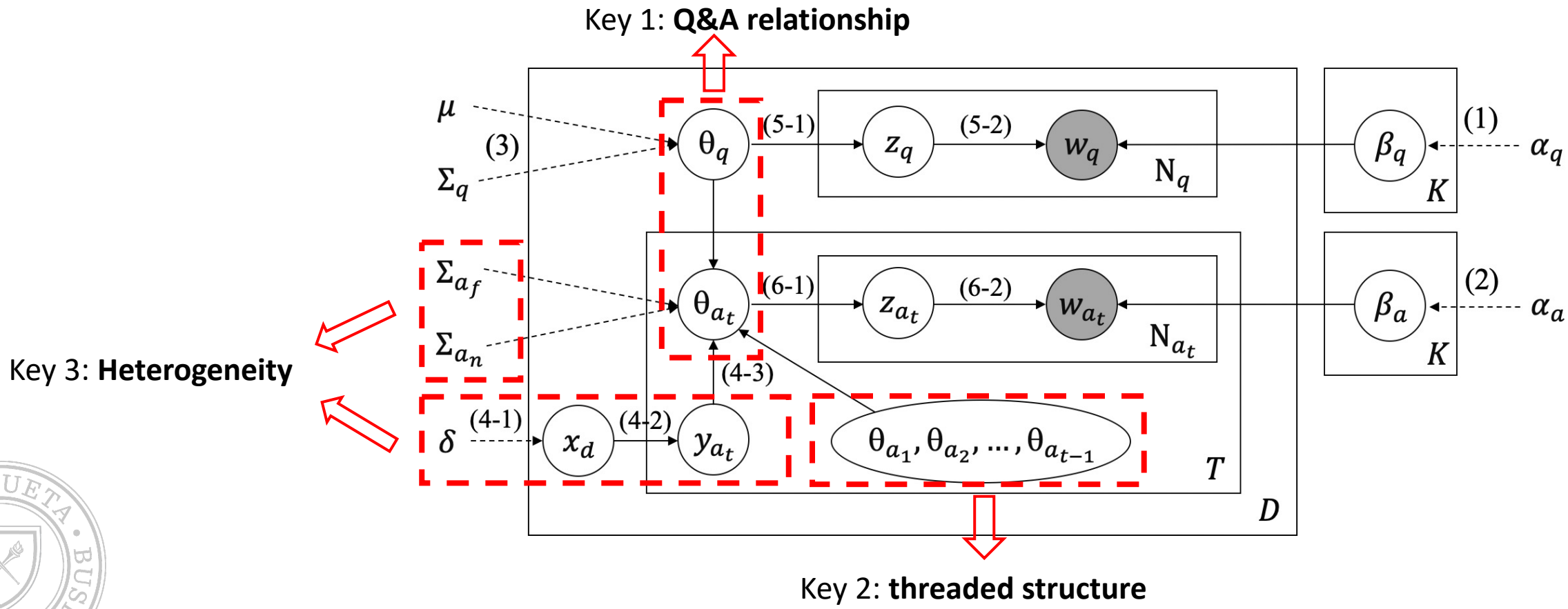
Depend on prior answers? ⇨ Yes: Follow-up answer; No: Novel answer

**(3) Heterogeneous impacts**

Question, Prior answers ⟶ Current answer

# 2 Model development: Our novel framework

- **Develop a novel unsupervised Bayesian topic modeling framework**



# 2 Model development: Inference and estimation

- **Complex model inference and estimation under high interdependencies**
  - Model inference
    - Variational mean-field inference and coordinate ascent algorithm
    - Maximize the evidence lower bound (ELBO)

$$\log p(\boldsymbol{w}_q,\boldsymbol{w}_{a_{1:T}};\boldsymbol{\mu},\boldsymbol{\Sigma}_q,\boldsymbol{\Sigma}_{a_f},\boldsymbol{\Sigma}_{a_n},\gamma,\boldsymbol{\delta},\boldsymbol{\alpha}_q,\boldsymbol{\alpha}_a) \geq E_u[\log p(\boldsymbol{\eta}_q;\boldsymbol{\mu},\boldsymbol{\Sigma}_q)] + \sum_{n_q=1}^{N_q} E_u\left[\log p\left(z_q^{n_q}\middle|\boldsymbol{\eta}_q\right)\right]$$
$$+ \sum_{n_q=1}^{N_q} E_u\left[\log p\left(w_q^{n_q}\middle|z_q^{n_q},\boldsymbol{\beta}_q^{1:K}\right)\right] + \sum_{k=1}^{K} E_u[\log p(\boldsymbol{\beta}_q^k;\boldsymbol{\alpha}_q)] + E_u[\log p(\boldsymbol{x}_d;\boldsymbol{\delta})]$$
$$+ \sum_{t=1}^{T} E_u[\log p(\boldsymbol{y}_{a_t}|\boldsymbol{x}_d)] + \sum_{t=1}^{T} E_u[\log p(\boldsymbol{\eta}_{a_t}|\boldsymbol{\eta}_q,\bar{\boldsymbol{\eta}}_{a_{t-1}},\boldsymbol{y}_{a_t};\boldsymbol{\Sigma}_{a_f},\boldsymbol{\Sigma}_{a_n},\gamma)]$$
$$+ \sum_{t=1}^{T}\sum_{n_{a_t}=1}^{N_{a_t}} E_u\left[\log p\left(z_{a_t}^{n_{a_t}}\middle|\boldsymbol{\eta}_{a_t}\right)\right] + \sum_{t=1}^{T}\sum_{n_{a_t}=1}^{N_{a_t}} E_u\left[\log p\left(w_{a_t}^{n_{a_t}}\middle|z_{a_t}^{n_{a_t}},\boldsymbol{\beta}_a^{1:K}\right)\right]$$
$$+ \sum_{k=1}^{K} E_u[\log p(\boldsymbol{\beta}_a^k;\boldsymbol{\alpha}_a)] + H(u),$$

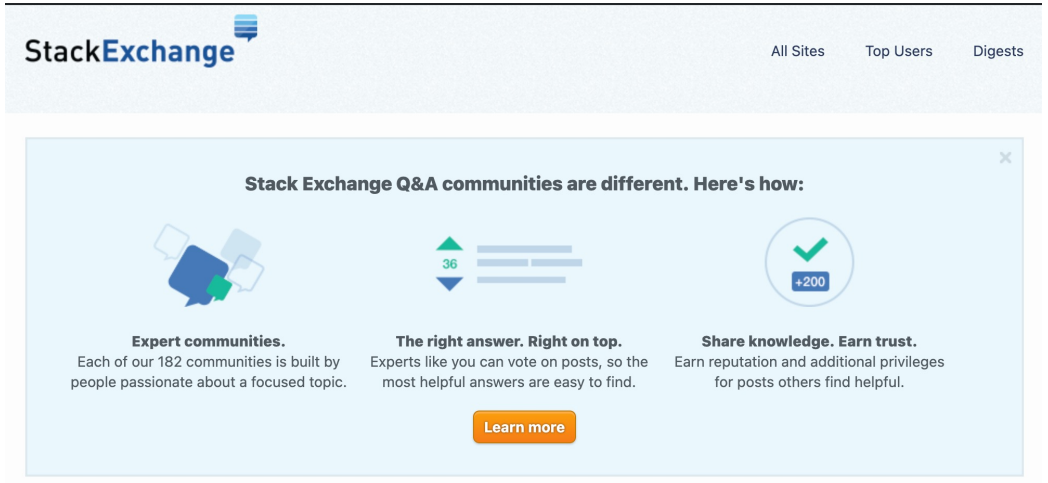
$$u(\boldsymbol{\eta}_q,\boldsymbol{\eta}_{a_{1:T}},\boldsymbol{x}_d,\boldsymbol{y}_{a_{1:T}},\boldsymbol{z}_q,\boldsymbol{z}_{a_{1:T}},\boldsymbol{\beta}_q,\boldsymbol{\beta}_a)$$
$$= \prod_{k=1}^{K} u\left(\eta_q^k;\lambda_q^k,(\sigma_q^k)^2\right)\prod_{t=1}^{T}\prod_{k=1}^{K} u\left(\eta_{a_t}^k;\lambda_{a_t}^k,(\sigma_{a_t}^k)^2\right) u(\boldsymbol{x}_d;\boldsymbol{\nu}_d)\prod_{t=1}^{T} u(\boldsymbol{y}_{a_t};\boldsymbol{\psi}_{a_t})$$
$$\prod_{n_q=1}^{N_q} u\left(z_q^{n_q};\boldsymbol{\phi}_q^{n_q}\right)\prod_{t=1}^{T}\prod_{n_{a_t}=1}^{N_{a_t}} u\left(z_{a_t}^{n_{a_t}};\boldsymbol{\phi}_{a_t}^{n_{a_t}}\right)\prod_{k=1}^{K} u(\boldsymbol{\beta}_q^k;\boldsymbol{\tau}_q^k)\prod_{k=1}^{K} u(\boldsymbol{\beta}_a^k;\boldsymbol{\tau}_a^k).$$

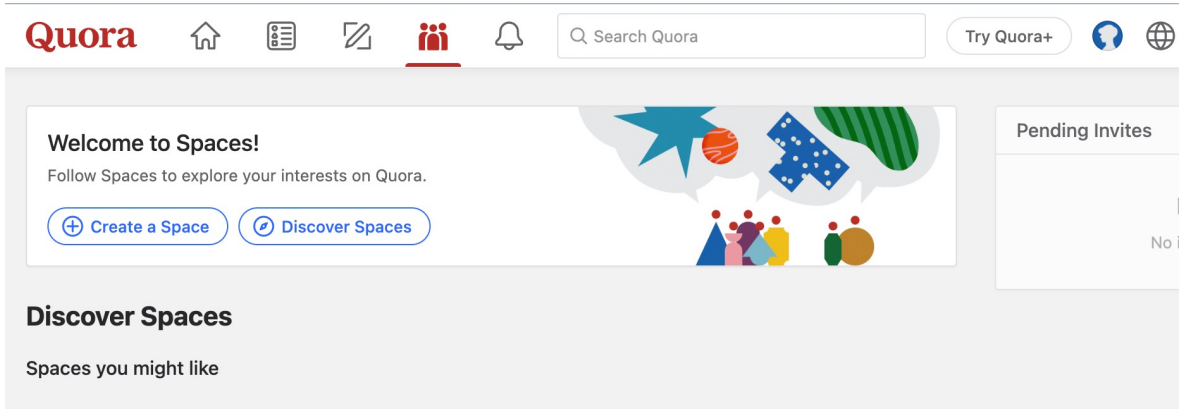
  - Parameter estimation
    - Variational expectation-maximization (VEM)
    - Maximize the likelihood bound

$$L\left(\boldsymbol{\mu},\boldsymbol{\Sigma}_q,\boldsymbol{\Sigma}_{a_f},\boldsymbol{\Sigma}_{a_n},\gamma;\boldsymbol{w}_{\boldsymbol{1:D},q},\boldsymbol{w}_{\boldsymbol{1:D},a_{1:T}}\right) \geq \hat{L}$$
$$= \sum_{d=1}^{D}\{E_{u_d}[\log p(\boldsymbol{\eta}_{d,q},\boldsymbol{\eta}_{d,a_{1:T}},\boldsymbol{x}_d,\boldsymbol{y}_{d,a_{1:T}},\boldsymbol{z}_{d,q},\boldsymbol{z}_{d,a_{1:T}},\boldsymbol{\beta}_q,\boldsymbol{\beta}_a,\boldsymbol{w}_{d,q},\boldsymbol{w}_{d,a_{1:T}})]$$
$$+ H(u_d)\}.$$

# 3 Model evaluation: Datasets

- **Real-world datasets**
  - Stack Exchange, 6 categories
  - Quora, 3 categories



# 3 Model evaluation: Datasets

- **Real-world datasets**
  - Stack Exchange, 6 categories
  - Quora, 3 categories

**Number of Q&A threads: 1,000 ~ 100,000**

Descriptive statistics of the Stack Exchange dataset

| Section (Category) | # of questions | # of answers | # of words per question/answer |
|---|---|---|---|
| Technology (Data Science) | 20740 | 31181 | 73.10 |
| Culture/Recreation (English Language & Usage) | 109977 | 268356 | 47.45 |
| Life/Arts (Cooking) | 23387 | 58078 | 57.49 |
| Science (Computer Science) | 31156 | 45807 | 72.49 |
| Professional (Writing) | 10429 | 34116 | 77.61 |
| Business (Project Management) | 5782 | 17724 | 70.26 |

Descriptive statistics of the Quora dataset

| Section (Category) | # of questions | # of answers | # of words per question/answer |
|---|---|---|---|
| Science and Technology | 1471 | 3144 | 28.82 |
| Business and Marketing | 1140 | 1981 | 23.50 |
| Health and Life | 2281 | 4144 | 20.18 |

# 3 Model evaluation: Statistical model fit

- Perplexity: based on **log-likelihood** (Blei et al. 2003; Roberts et al. 2019)

**How "perplexed" the model is?**

$$perplexity = \exp\left\{-\frac{\log p(\boldsymbol{w})}{\sum_{d}^{|D_{test}|}\sum_{v=1}^{V} num_{d}^{v}}\right\}$$

Lower perplexity ⇨ Higher likelihood ⇨ Better model fit / generalizability

# 3 Model evaluation: Statistical model fit

- Perplexity: based on **log-likelihood** (Blei et al. 2003; Roberts et al. 2019)

Lower perplexity ⇨ Higher likelihood ⇨ Better model fit / generalizability

Perplexity comparison for the Stack Exchange dataset

| Model | Technology (Data Science) | Culture/ Recreation (English Language & Usage) | Life/Arts (Cooking) | Science (Computer Science) | Professional (Writing) | Business (Project Management) |
|---|---|---|---|---|---|---|
| LDA | 1152.11 | 2181.84 | 1520.59 | 1063.53 | 1726.48 | 1087.31 |
| NTM | 1021.39 | 2176.38 | 1407.79 | 1028.45 | 1639.31 | 1063.06 |
| TRTM | 1029.95 | 2030.30 | 1296.18 | 976.34 | 1727.38 | 998.90 |
| STM | 1054.08 | 2015.43 | 1271.62 | 975.40 | 1718.43 | 1010.79 |
| SCHOLAR | 951.94 | 1586.73 | 1251.94 | 934.26 | 1615.01 | 1037.08 |
| QATM | 931.21 | 1625.43 | 1297.68 | 958.23 | 1479.63 | 939.54 |
| LeadLDA1 | 1256.93 | 1702.28 | 1376.98 | 1063.31 | 1512.57 | 956.25 |
| LeadLDA2 | 1100.50 | 1707.15 | 1326.48 | 1075.64 | 1498.23 | 1064.47 |
| SITS | 1008.46 | 1635.08 | 1280.41 | 979.68 | 1482.28 | 934.51 |
| TM-OKC (mean) | **863.44**$^{***}$ | 1591.63 | 1220.97 | 891.59 | 1400.93 | 901.03 |
| TM-OKC (decay) | 863.93 | **1582.44** | 1221.01 | **891.30**$^{***}$ | 1394.29 | **899.39**$^{***}$ |
| TM-OKC (weight) | 867.69 | 1591.73 | **1218.70**$^{***}$ | 892.54 | **1390.96**$^{***}$ | 900.59 |

Perplexity comparison for the Quora dataset

| Model | Science and Technology | Business and Marketing | Health and Life |
|---|---|---|---|
| LDA | 1579.54 | 1698.37 | 1357.71 |
| NTM | 1204.54 | 1368.05 | 1083.70 |
| TRTM | 1131.22 | 1310.21 | 1104.22 |
| STM | 1117.93 | 1301.27 | 1109.51 |
| SCHOLAR | 1192.71 | 1321.77 | 1087.89 |
| QATM | 1033.00 | 1243.23 | 1065.07 |
| LeadLDA1 | 1399.21 | 1227.56 | 1088.73 |
| LeadLDA2 | 1350.26 | 1242.85 | 1132.91 |
| SITS | 1313.06 | 1264.70 | 1058.69 |
| TM-OKC (mean) | **1014.30**$^{***}$ | **1202.66**$^{***}$ | 1042.97 |
| TM-OKC (decay) | 1015.86 | 1212.19 | 1040.38 |
| TM-OKC (weight) | 1018.13 | 1215.98 | **1032.61**$^{***}$ |

# 3 Model evaluation: Statistical model fit

- Coherence score
  - "Similarity" (word co-occurrences) of the top words within a topic
  - Higher score indicates the learned topics are more coherent (Syed and Spruit 2017; Dieng et al. 2020)

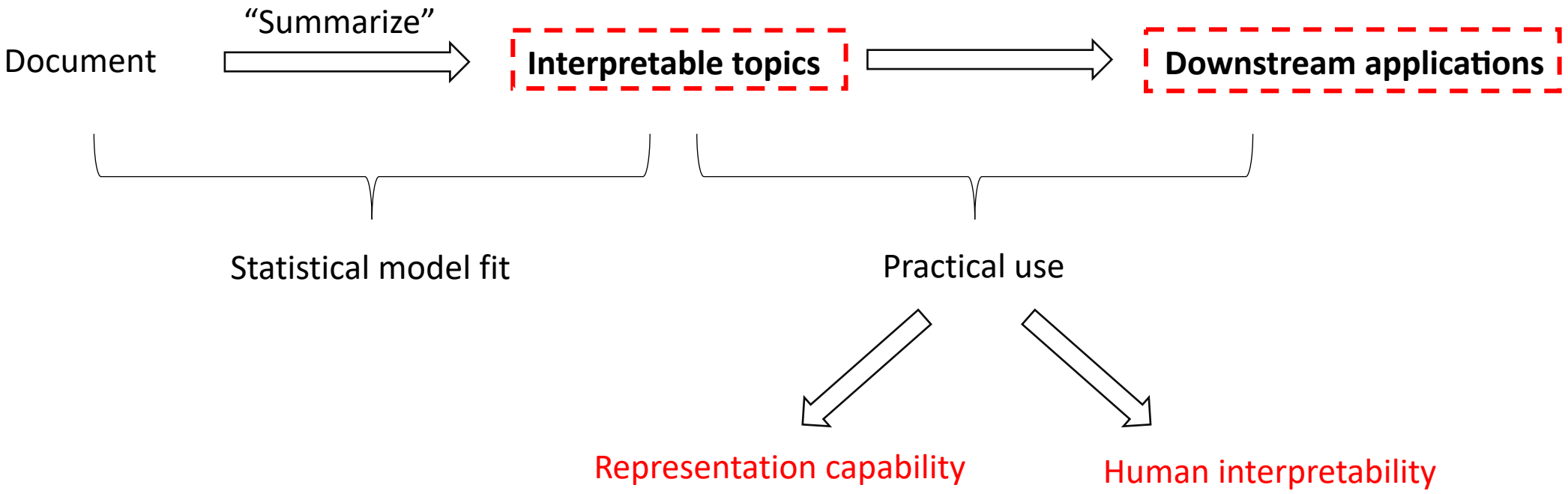
Coherence comparison for the Stack Exchange dataset

| Model | Technology (Data Science) | Culture/ Recreation (English Language & Usage) | Life/Arts (Cooking) | Science (Computer Science) | Professional (Writing) | Business (Project Management) |
|---|---|---|---|---|---|---|
| LDA | 0.51 | 0.42 | 0.47 | 0.47 | 0.37 | 0.37 |
| NTM | 0.53 | 0.43 | 0.47 | 0.48 | 0.37 | 0.39 |
| TRTM | 0.51 | 0.42 | 0.46 | 0.48 | 0.37 | 0.36 |
| STM | 0.53 | 0.41 | 0.48 | 0.49 | **0.39** | 0.37 |
| SCHOLAR | 0.53 | 0.43 | 0.48 | 0.49 | 0.37 | 0.37 |
| QATM | 0.52 | 0.42 | 0.48 | 0.48 | 0.37 | **0.42** |
| LeadLDA1 | 0.50 | 0.40 | 0.47 | 0.47 | 0.35 | 0.36 |
| LeadLDA2 | 0.51 | 0.40 | 0.46 | 0.48 | 0.36 | 0.37 |
| SITS | 0.52 | 0.41 | 0.47 | 0.48 | 0.38 | 0.39 |
| TM-OKC (mean) | 0.53 | **0.45**$^{*}$ | **0.50**$^{*}$ | **0.51**$^{**}$ | **0.39** | **0.42** |
| TM-OKC (decay) | 0.53 | 0.43 | **0.50**$^{*}$ | **0.51**$^{**}$ | 0.38 | 0.41 |
| TM-OKC (weight) | **0.56**$^{***}$ | 0.44 | **0.50**$^{*}$ | **0.51**$^{**}$ | 0.38 | 0.41 |

Coherence comparison for the Quora dataset

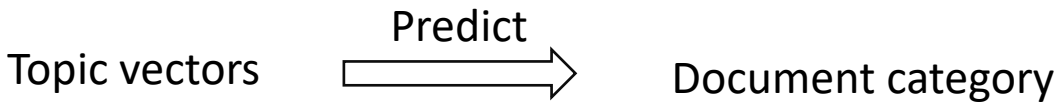
| Model | Science and Technology | Business and Marketing | Health and Life |
|---|---|---|---|
| LDA | 0.40 | 0.39 | 0.41 |
| NTM | 0.46 | 0.41 | 0.42 |
| TRTM | 0.42 | 0.42 | 0.42 |
| STM | 0.43 | 0.43 | 0.43 |
| SCHOLAR | 0.45 | 0.40 | 0.42 |
| QATM | 0.43 | 0.44 | 0.42 |
| LeadLDA1 | 0.46 | 0.38 | 0.44 |
| LeadLDA2 | 0.41 | 0.39 | 0.42 |
| SITS | 0.43 | 0.41 | 0.43 |
| TM-OKC (mean) | **0.48**$^{**}$ | 0.45 | **0.47**$^{***}$ |
| TM-OKC (decay) | 0.47 | **0.46**$^{**}$ | 0.46 |
| TM-OKC (weight) | **0.48**$^{**}$ | 0.45 | 0.46 |

# 3 Model evaluation: More direct evaluation



# 3 Model evaluation: Representation capability

- *Document classification* task (Zeng et al. 2019; Yang et al. 2022)

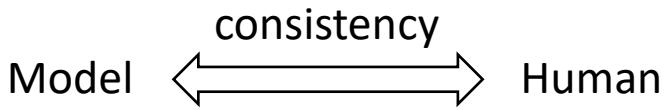



Prediction accuracy of different methods

| | | Stack Exchange | | | Quora | | |
|---|---|---|---|---|---|---|---|
| | Number of topics | 40 | 80 | 120 | 40 | 80 | 120 |
| Basic text feature extraction methods | TF-IDF features (top 100 words) | | 0.517 | | | 0.600 | |
| | TF-IDF features (top 500 words) | | 0.717 | | | 0.779 | |
| | TF-IDF features (top 1000 words) | | 0.718 | | | 0.804 | |
| Bayesian topic modeling methods | LDA | 0.727 | 0.710 | 0.699 | 0.728 | 0.726 | 0.712 |
| | TRTM | 0.891 | 0.885 | 0.893 | 0.935 | 0.920 | 0.937 |
| | STM | 0.886 | 0.847 | 0.888 | 0.935 | 0.935 | 0.930 |
| | QATM | 0.898 | 0.853 | 0.860 | 0.960 | 0.962 | 0.937 |
| | LeadLDA1 | 0.867 | 0.832 | 0.751 | 0.762 | 0.749 | 0.747 |
| | LeadLDA2 | 0.865 | 0.865 | 0.749 | 0.796 | 0.762 | 0.737 |
| | SITS | 0.903 | 0.891 | 0.868 | 0.881 | 0.893 | 0.876 |
| Topic modeling combined with deep language models | NTM | 0.905 | 0.900 | 0.859 | 0.813 | 0.827 | 0.848 |
| | SCHOLAR | 0.901 | 0.903 | 0.885 | 0.826 | 0.855 | 0.818 |
| Representation learning methods | Bi-LSTM | | 0.822 | | | 0.919 | |
| | Pre-trained BERT | | 0.696 | | | 0.722 | |
| | Fine-tuned BERT | | 0.936 | | | 0.992 | |
| Our method | TM-OKC | $0.911^{*}$ | $0.933^{***}$ | $0.918^{***}$ | $0.983^{**}$ | $0.990^{***}$ | $0.968^{***}$ |

# 3 Model evaluation: Interpretability

- Lab studies
  - *word intrusion* and *topic intrusion* tasks (Chang et al. 2009; Bao and Datta 2014; Palese and Piccoli 2020)




Human evaluation results of *word intrusion* and *topic intrusion* tasks

| Number of topics | $WIP_m$ in *word intrusion* | | | $TLO_m$ in *topic intrusion* | | |
|---|---|---|---|---|---|---|
| | 40 | 80 | 120 | 40 | 80 | 120 |
| LDA | 0.806 | 0.794 | 0.788 | -1.61 | -1.65 | -1.85 |
| NTM | 0.825 | 0.813 | 0.819 | -1.52 | -1.47 | -1.48 |
| TRTM | 0.813 | 0.838 | 0.806 | -1.43 | -1.35 | -1.49 |
| STM | 0.819 | 0.825 | 0.819 | -1.37 | -1.25 | -1.47 |
| SCHOLAR | 0.813 | 0.819 | 0.813 | -1.36 | -1.30 | -1.51 |
| QATM | 0.825 | 0.831 | 0.813 | -1.31 | -1.22 | -1.39 |
| SITS | 0.819 | 0.825 | 0.800 | -1.32 | -1.29 | -1.38 |
| LeadLDA1 | 0.813 | 0.806 | 0.800 | - | - | - |
| LeadLDA2 | 0.819 | 0.813 | 0.794 | - | - | - |
| TM-OKC | $0.856^{**}$ | $0.869^{**}$ | $0.838^{*}$ | $-1.12^{**}$ | $-0.96^{***}$ | $-1.23^{**}$ |

# 4 Downstream applications

Statistical model fit

Representation capability

Interpretability

A better topic model

User profiling

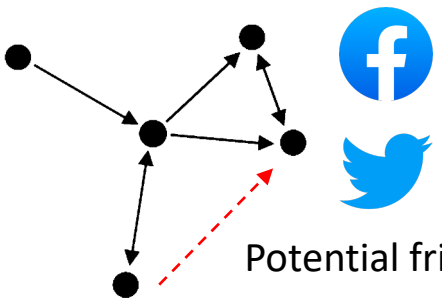
Friendship suggestion

… … …

Trending topic detection

User interests' discovery

User A: football fan
User B: foodie
… …



Potential friend

Analyzing customer reviews

- CRM
- Brand perception
- Product design

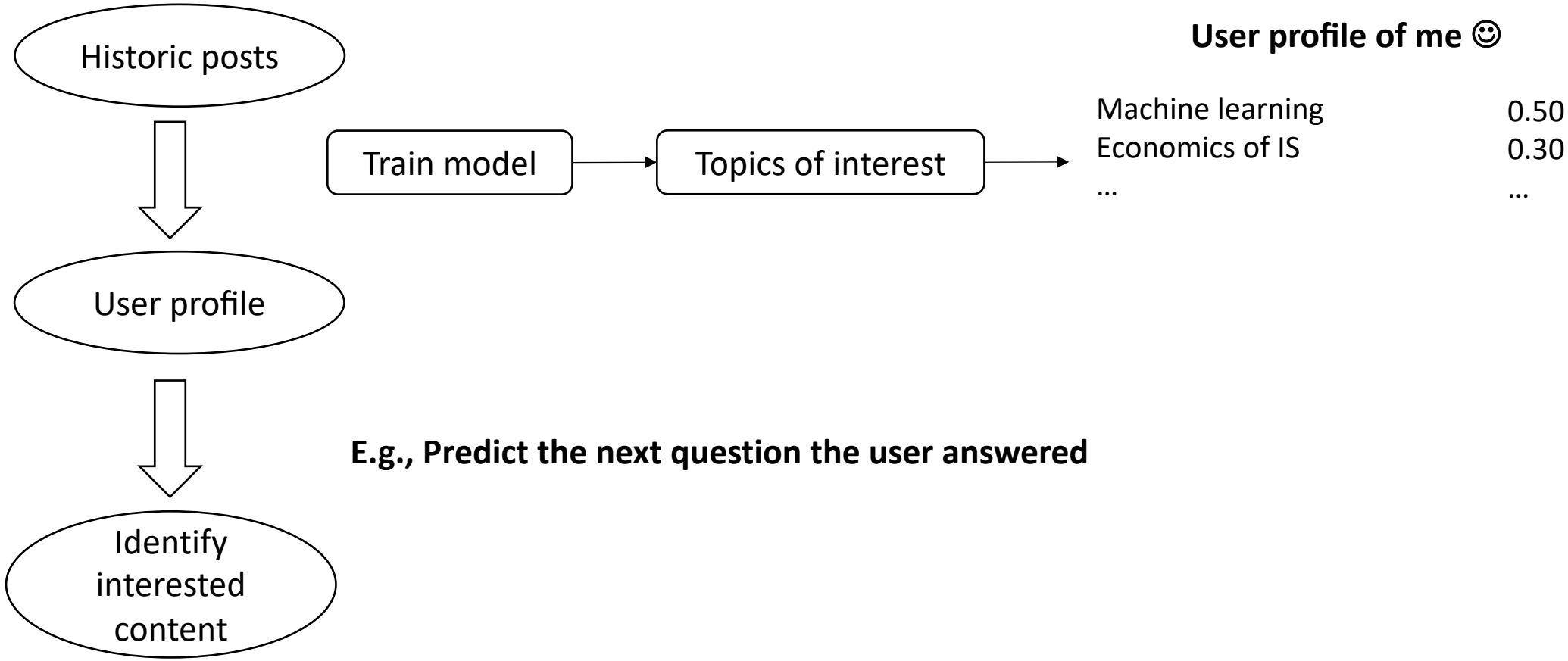
(Geva et al. 2019, *MIS Quarterly*)

(Li et al. 2016, *Management Science*)

(Büschken and Allenby 2020, *Marketing Science*)

# 4 Downstream applications

- **Example: user profiling**
  - User interests' discovery (He et al. 2017; Dhillon and Aral 2021)



# 4 Downstream applications

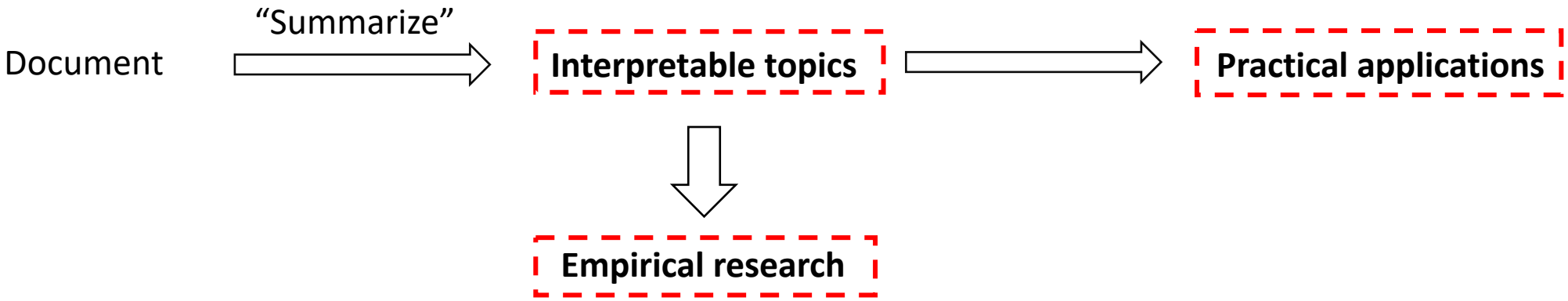
- **Example: user profiling**
  - User interests' discovery (He et al. 2017; Dhillon and Aral 2021)

User profiling performance comparison of different methods

| | | Hit rate for top $K$ | | |
|---|---|---|---|---|
| | | $K$=5 | $K$=10 | $K$=20 |
| Basic text feature extraction methods | TF-IDF features (top 100 words) | 5.1% | 11.7% | 21.4% |
| | TF-IDF features (top 500 words) | 5.3% | 11.5% | 21.2% |
| | TF-IDF features (top 1000 words) | 5.5% | 11.8% | 21.6% |
| Bayesian topic modeling methods | LDA | 20.9% | 33.9% | 49.7% |
| | TRTM | 26.6% | 43.7% | 59.3% |
| | STM | 26.5% | 44.1% | 59.4% |
| | QATM | 26.5% | 45.2% | 60.1% |
| | LeadLDA1 | 6.2% | 11.7% | 22.1% |
| | LeadLDA2 | 6.5% | 12.8% | 24.1% |
| | SITS | 26.0% | 41.4% | 58.3% |
| Pre-trained deep language models | Pre-trained BERT | 8.6% | 14.9% | 26.6% |
| Topic modeling combined with deep language models | NTM | 18.2% | 32.1% | 42.8% |
| | SCHOLAR | 19.4% | 33.6% | 50.6% |
| Neural matrix factorization | NMF | 19.0% | 32.1% | 46.0% |
| **Our method** | TM-OKC | 32.6%*** | 49.1%** | 64.8%** |

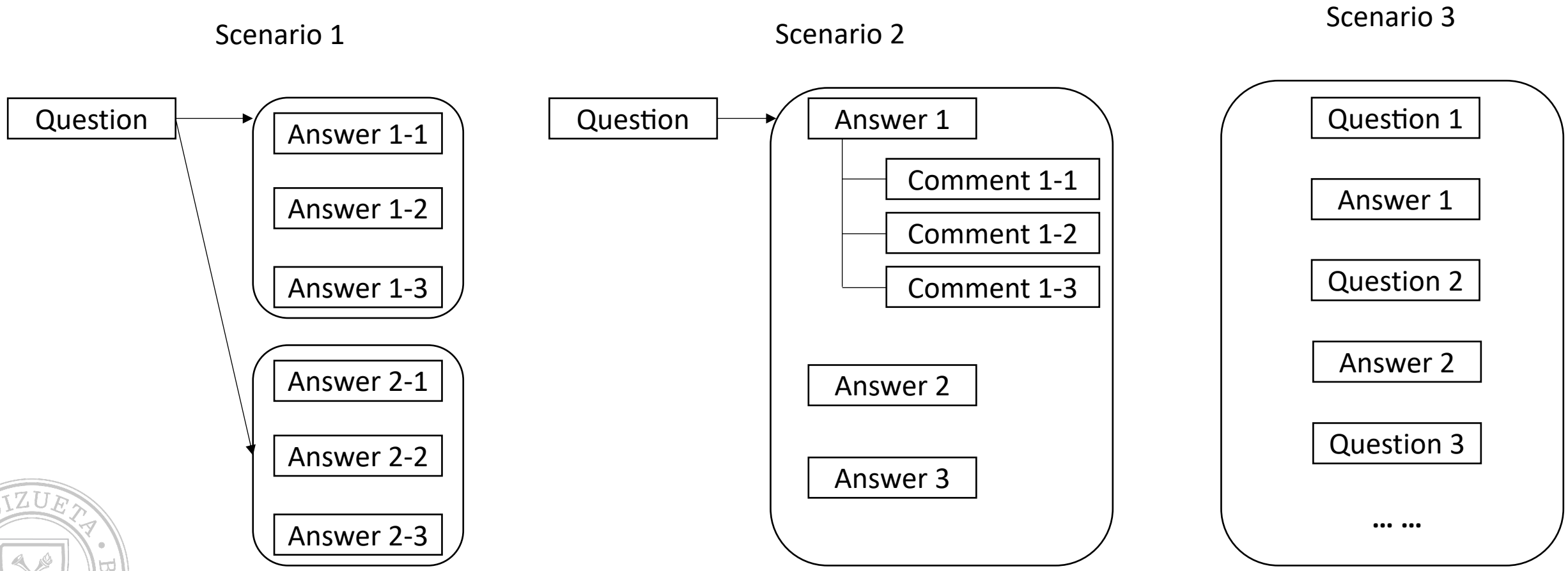
| | | Data size $N$ (number of Q&A threads) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1,000 | 2,000 | 4,000 | 8,000 | 16,000 | 32,000 | 64,000 |
| Basic text feature extraction methods | TF-IDF features (top 100 words) | 10.5% | 10.7% | 11.1% | 11.7% | 11.1% | 12.4% | 12.2% |
| | TF-IDF features (top 500 words) | 10.3% | 10.6% | 11.5% | 11.5% | 11.8% | 11.3% | 11.5% |
| | TF-IDF features (top 1000 words) | 10.6% | 10.4% | 11.9% | 11.8% | 11.2% | 11.2% | 11.7% |
| Bayesian topic modeling methods | LDA | 26.9% | 29.6% | 31.5% | 33.9% | 34.8% | 35.9% | 36.4% |
| | TRTM | 37.7% | 39.8% | 40.5% | 43.7% | 44.3% | 45.1% | 45.1% |
| | STM | 36.4% | 40.9% | 42.0% | 44.1% | 44.9% | 45.2% | 45.6% |
| | QATM | 30.0% | 35.0% | 40.0% | 45.2% | 45.7% | 45.3% | 46.0% |
| | LeadLDA1 | 10.2% | 10.1% | 10.7% | 11.7% | 12.2% | 14.8% | 15.2% |
| | LeadLDA2 | 10.5% | 10.6% | 10.6% | 12.8% | 12.1% | 15.4% | 15.9% |
| | SITS | 34.5% | 40.1% | 39.8% | 41.4% | 43.9% | 44.7% | 45.8% |
| Pre-trained deep language models | Pre-trained BERT | 13.3% | 14.1% | 13.4% | 14.9% | 14.6% | 13.6% | 14.1% |
| Topic modeling combined with deep language models | NTM | 15.5% | 23.6% | 27.0% | 32.1% | 41.7% | 47.2% | 50.6% |
| | SCHOLAR | 20.4% | 22.5% | 28.8% | 33.6% | 42.6% | 47.8% | 51.4% |
| Neural matrix factorization | NMF | 20.8% | 23.7% | 27.8% | 32.1% | 40.8% | 46.7% | 49.8% |
| **Our method** | TM-OKC | 46.8%*** | 47.7%*** | 48.0%*** | 49.1%** | 49.7%** | 50.1%* | 51.3% |

# 4 Downstream applications



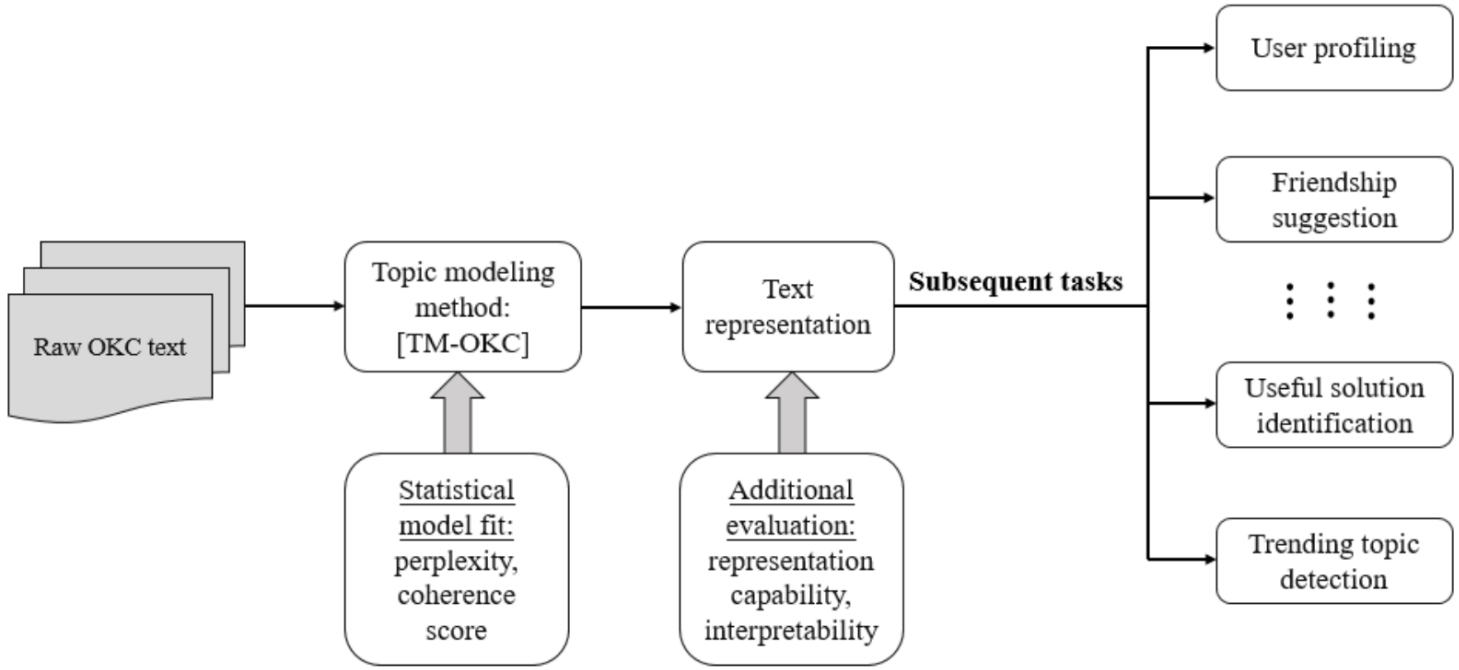

- **Topics as "independent variables"** (Yue et al. 2019, *MIS Quarterly*; Narang et al. 2022, *Journal of Marketing Research*; Gour et al. 2022, *Production and Operations Management*)
- **Topics as "dependent variables"** (Singh et al. 2014, *Information Systems Research*; Tirunillai and Tellis 2014, *Journal of Marketing Research*; Geva et al. 2019, *MIS Quarterly*)
- **Topics used to derive new variables** (Ghose et al. 2019, *Management Science*; Pu et al. 2022, *Information Systems Research*; Bachura et al. 2022, *MIS Quarterly*)

# 5 Model extensions

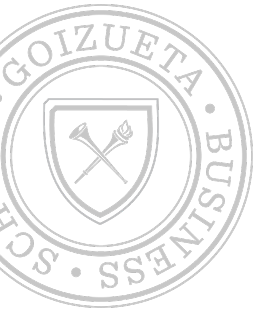


# 6 Summary

- Develop a novel unsupervised Bayesian topic modeling framework
  - Complex Q&A relations and threaded structures among texts with heterogeneity
- Superior performance
  - Statistical model fit, representation capability, and human interpretability
- Implications to IS researchers and practitioners in downstream empirical studies and practical tasks

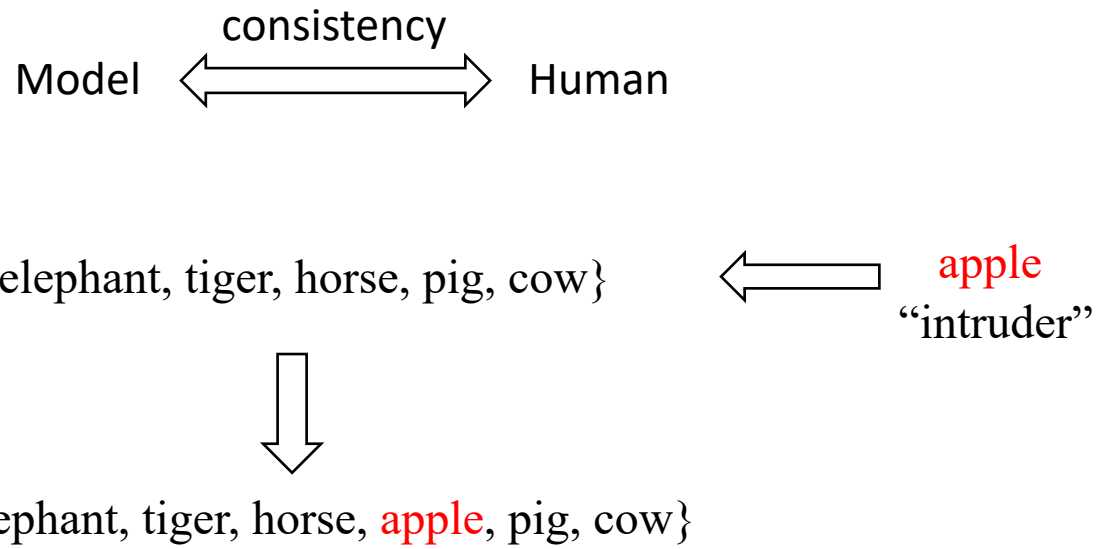


Thank you very much!



# Appendix: Human interpretability

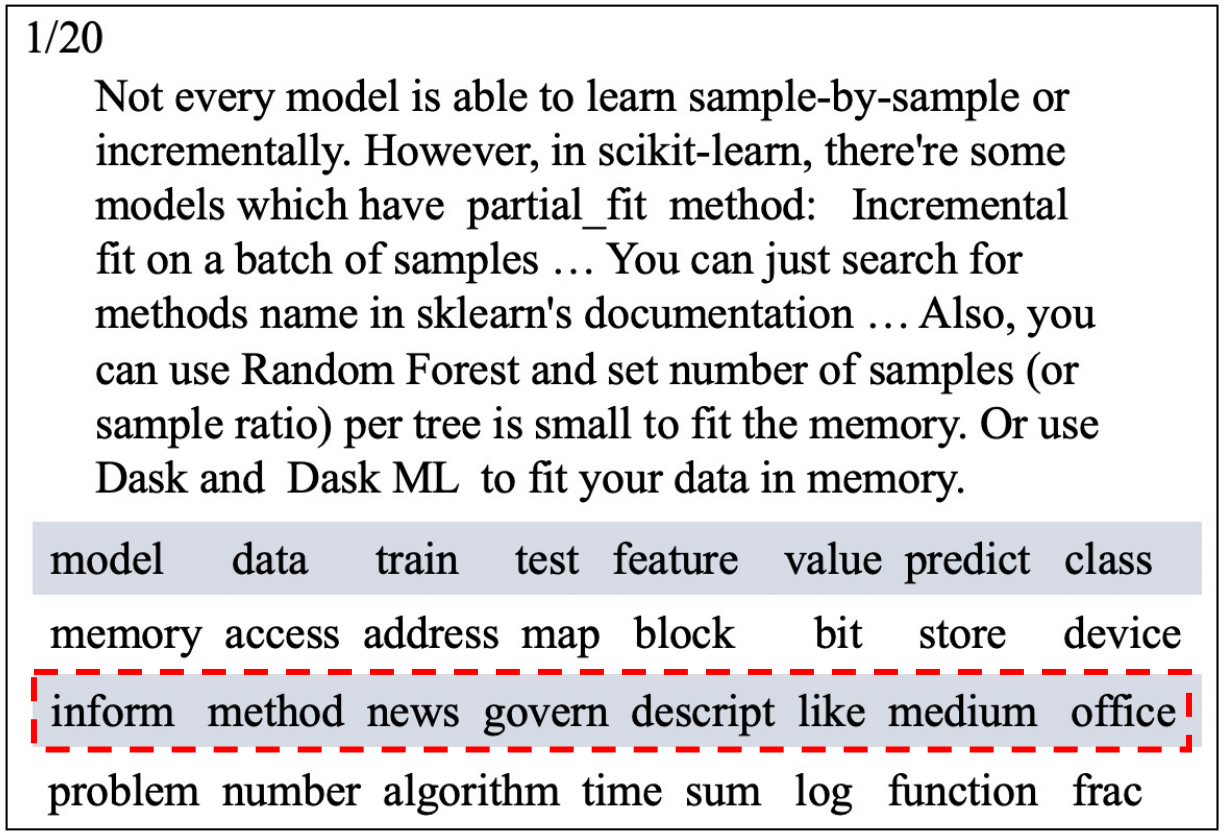
- Well-known lab studies
  - *Word intrusion* and *topic intrusion* tasks (Chang et al. 2009; Bao and Datta 2014; Palese and Piccoli 2020)
  - Amazon Mechanical Turk (MTurk)




*word intrusion* example

# Appendix: Human interpretability

- Well-known lab studies
  - *Word intrusion* and *topic intrusion* tasks (Chang et al. 2009; Bao and Datta 2014; Palese and Piccoli 2020)
  - Amazon Mechanical Turk (MTurk)




*topic intrusion* example