CrowdQM: Learning aspect-level user reliability and comment trustworthiness in discussion forums

Alex Morales, Kanika Narang, Hari Sundaram, and Chengxiang Zhai
{amorale4, knarang2, hs1, czhai}@Illinois.edu

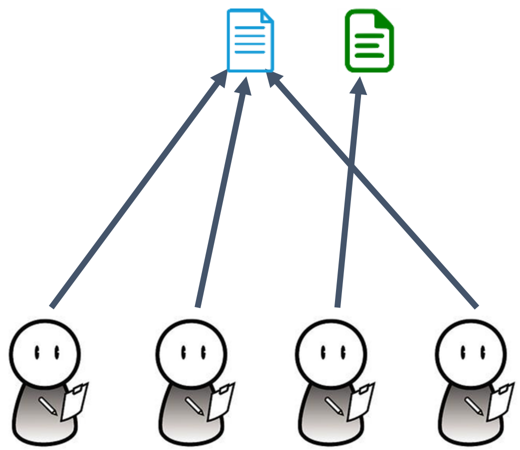
Modeling user's expertise via commenting patterns

- More information than the comments users leave

- Not all comments are of equal quality
- User may have expertise in specialized topics
- How can we use language to model fine-grained expertise?

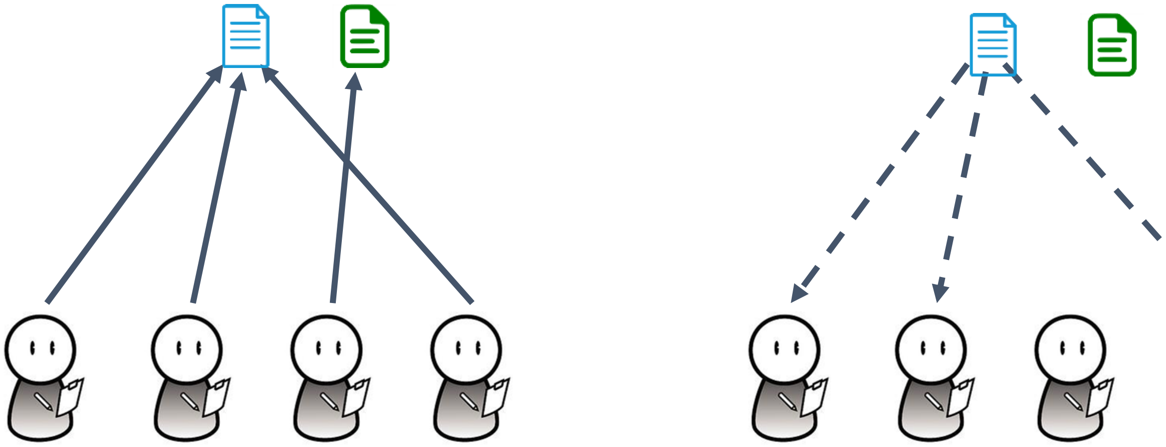
Truth-Discovery Principle

- **Truth-Discovery principle**: the answers written by reliable users tend to be more trustworthy, while the users who have given trustworthy answers are more likely to be reliable



Truth-Discovery Principle

- **Truth-Discovery principle**: the answers written by reliable users tend to be more trustworthy, while the users who have given trustworthy answers are more likely to be reliable



Example:

- **Finding a diagnosis:**

m: headache, chills, fever

Example:

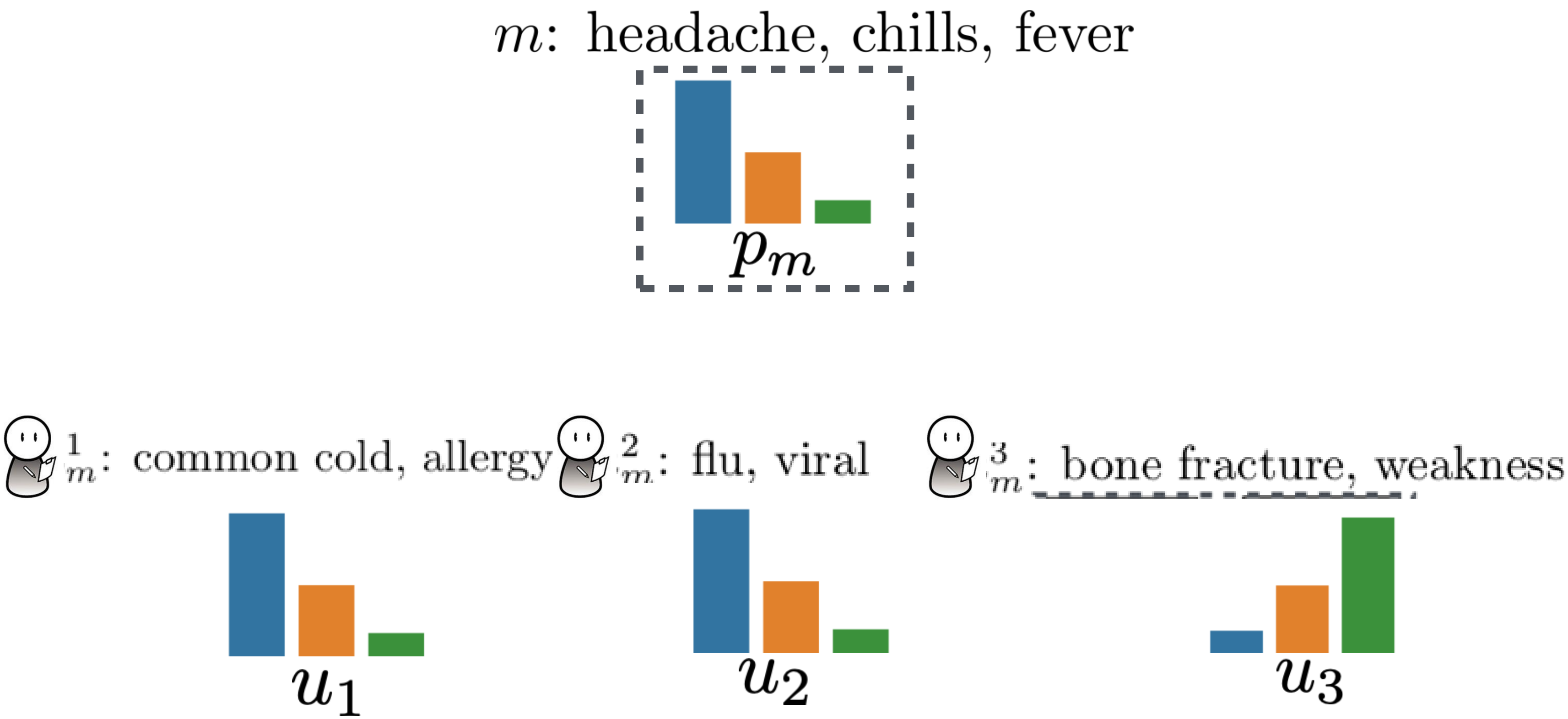
- User-post comments

m: headache, chills, fever

^1_m: common cold, allergy ^2_m: flu, viral ^3_m: bone fracture, weakness

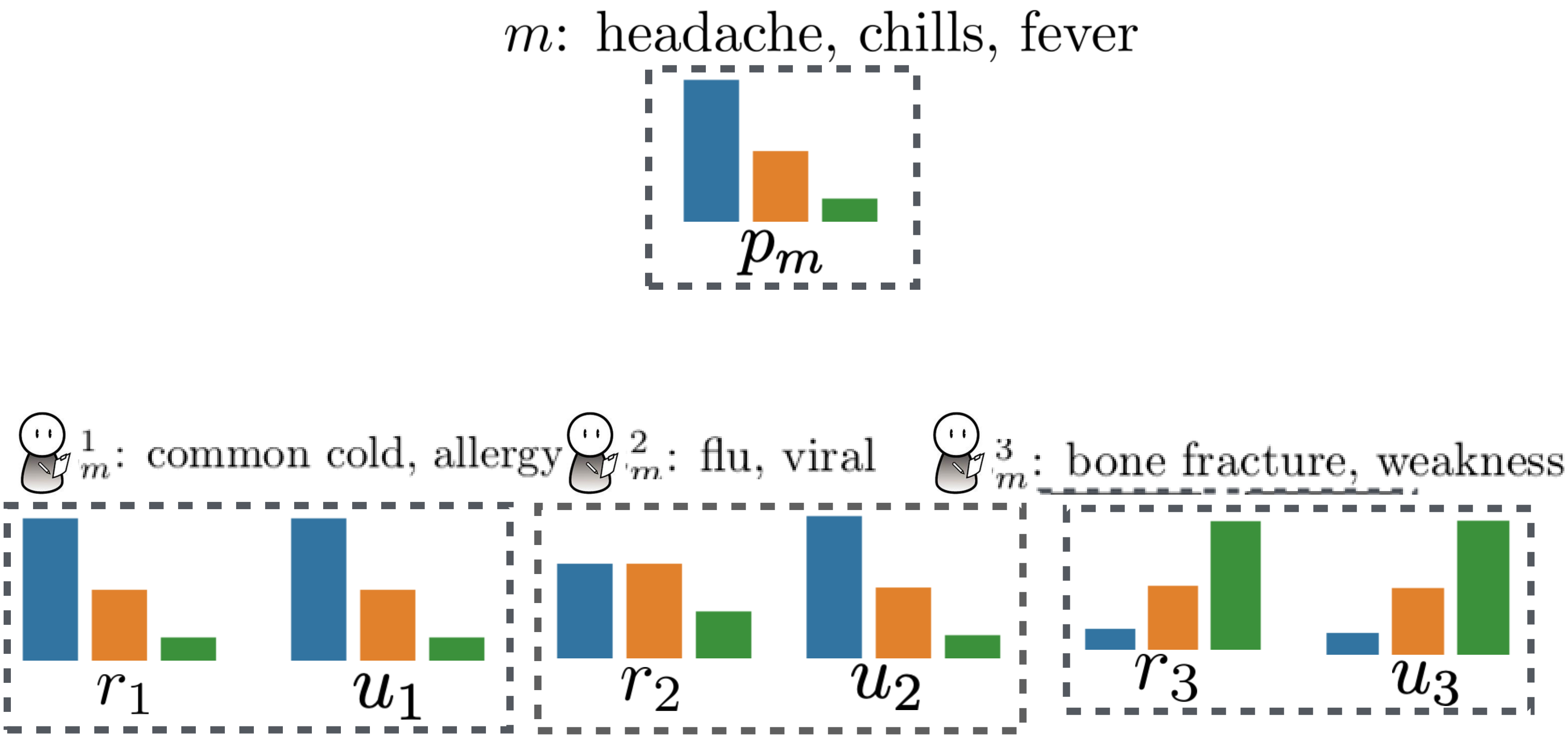
Example:

- Post/User-aspect distribution



Example:

- User aspect reliability



Modeling comment trustworthiness and user-aspect reliabilities

- For each post, m, a **latent trustworthy comment embeddings**, $\boldsymbol{a}_m^* \in \mathbb{R}^D$
  - Comment embedding error

$$E_{m,n}$$

- infer **user-aspect reliabilities** $\boldsymbol{r}_n \in \mathbb{R}^K$
  - User-post reliabilities

$$R_{m,n}$$

- **learn word embeddings** $\boldsymbol{v}_\omega \in \mathbb{R}^D$
  - Context Error

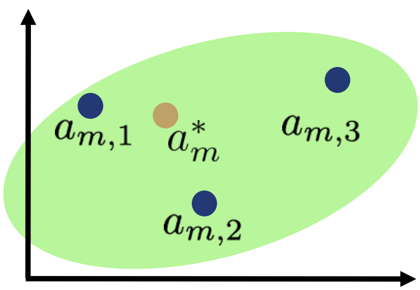
$$Q_{m,n}$$

Comment Embedding Error

- Learned trustworthy comment embeddings are similar learned to comment embeddings for the post

$$E_{m,n} = ||\boldsymbol{a}_m^* - \boldsymbol{a}_{m,n}||^2$$

Comment Embedding

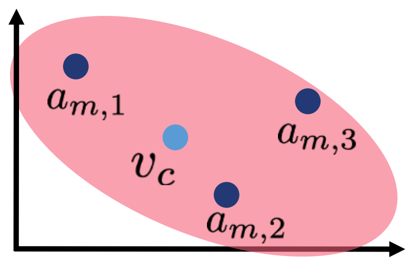


$$\boldsymbol{a}_{m,n} = |\boxed{w_{m,n}}|^{-1} \sum_{\omega \in w_{m,n}} \boldsymbol{v}_\omega$$

user n ’s comment on post m

Context Embedding Error

- Learned comment embeddings are similar learned to the context embedding of the post



$$Q_{m,n} = |\boxed{c_m}|^{-1} \sum_{c \in c_m} ||\boldsymbol{a}_{m,n} - \boldsymbol{v}_c||^2$$

set of words in post m

post word embedding

User-Post Reliability

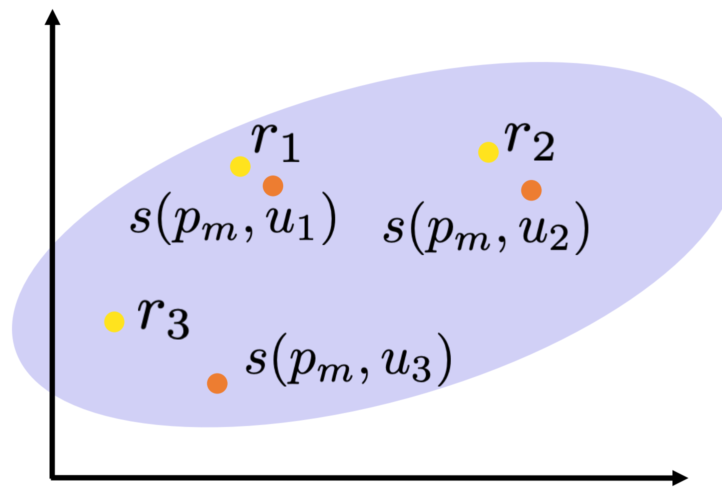
- User aspect similarity scores weighted by the user-aspect reliabilities

$$R_{m,n} = \sum_k \boldsymbol{r}_n^{(k)} \cdot (\boldsymbol{u}_n^{(k)} \cdot \boldsymbol{p}_m^{(k)})$$

reliability of aspect k for user n

Aspect k familiarity for user n

Aspect k weight for post m



Putting Everything Together

context error weight hyperparameter

$$\min_{\{\boldsymbol{a}_m^*\},\{\boldsymbol{v}_\omega\},\{\boldsymbol{r}_n\}} \sum_{n=1}^{N} \sum_{m \in \mathcal{M}_n} \underbrace{R_{m,n}}_{\text{user-post reliability}} \left(\underbrace{E_{m,n}}_{\text{embedding error}} + \beta \odot \underbrace{Q_{m,n}}_{\text{context error}} \right)$$

$$\text{s.t.} \sum_{n=1}^{N} e^{-\boldsymbol{r}_n^{(k)}} = 1; \forall k$$

posts which user n has commented on

Experiments and Dataset

- Reddit Dataset: crawled 3 Subreddit communities until Oct, 2017

	AskDocs	AskScience	AskHistorians
Number of users	3,334	73,463	27,463
Number of experts	286	2,195	296
Number of posts	17,342	100,237	45,264

Trustworthy Comment Identification Results

- Using the latent trustworthy comment embedding as a measure for trustworthiness (i.e. feature for ranking)
- Precision @ 1 with gold standard: Experts

Model	*Docs	*Science	*Historians
MBoA	0.592	0.633	0.602
CRH [12]	0.585	0.597	0.556
CATD [11]	**0.635**	0.700	0.669
TrustAnswer [14]	0.501	0.657	0.637
CrowdQM-no-aspect	0.509	0.666	0.640
CrowdQM	0.617	**0.734**	**0.753**

Trustworthy Comment Identification Results

- Using the latent trustworthy comment embedding as a measure for trustworthiness (i.e. feature for ranking)
- Precision @ 1 with gold standard: Upvotes

Model	*Docs	*Science	*Historians
MBoA	**0.434**	0.302	0.257
CRH [12]	0.386	0.234	0.183
CATD [11]	0.405	0.291	0.257
TrustAnswer [14]	0.386	0.373	0.449
CrowdQM-no-aspect	0.388	0.368	0.450
CrowdQM	0.426	**0.402**	**0.493**

Qualitative Study: User Expert Ranking

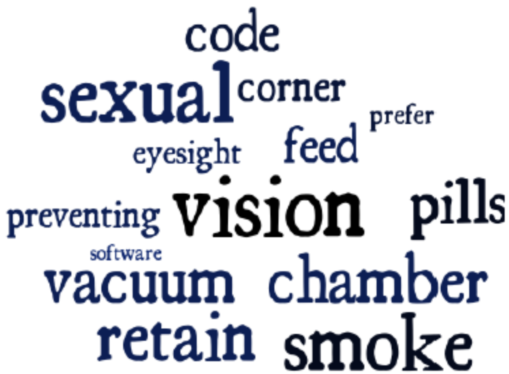
- Using user-post reliability score as a feature for expert finding

Post Category: Computing
Embedded Systems, Software Engineering, Robotics
Computer Science
Quantum Optics, Singular Optics
Robotics, Machine Learning, Computer Vision, Manipulators
Computer Science
Biomechanical Engineering, Biomaterials

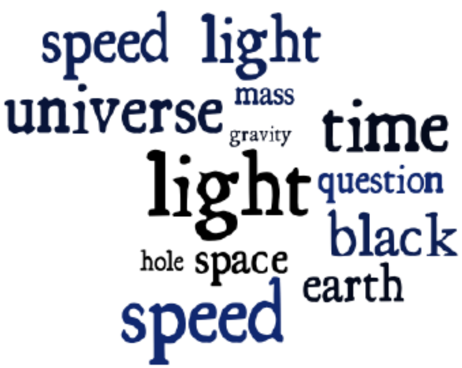
Post Category:Linguistics
Linguistics, Hispanic Sociolinguistics
Comparative Political Behaviour
Historical Linguistics, Language Documentation
Linguistics, Hispanic Sociolinguistics
Historical Linguistics, Language Documentation
Nanostructured Materials, Heterogeneous Catalysis

Qualitative Study: aspect terms on corresponding subject

- Correlate category specific user karma with reliability score to identify aspects relevant for that category



(a) Health



(b) Cosmos

(c) Oceanography

Qualitative Study: Word Embedding Similarity

- Word Embedding analysis: encoding trust-aware words

Liquid		Cancer		Quantum	
Initial	CrowdQM	Initial	CrowdQM	Initial	CrowdQM
unimaginably	gas	mg	disease	search results	model
bigger so	chemical	curie	white	sis	energy
two lenses	solid	wobbly	cell	shallower water	particle
orbiting around	air	subject	food	starts rolling	mechanics
fire itself	material	”yes” then	complete	antimatter galaxies	mathematical

Summary

- **Unsupervised model** for trustworthiness finding
- Model for **user-aspect reliabilities**
- Trust-aware word embeddings
- Qualitative study for expert ranking and word embedding similarity