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

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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.
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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

$m$: headache, chills, fever

$P_m$

$m_1$: common cold, allergy
$m_2$: flu, viral
$m_3$: bone fracture, weakness
Example:

- User aspect reliability

\( m: \) headache, chills, fever

\( p_m \)

\( \mu_1^1: \) common cold, allergy

\( \mu_2^2: \) flu, viral

\( \mu_3^3: \) bone fracture, weakness
Modeling comment trustworthiness and user-aspect reliabilities

- For each post, \(m\), a **latent trustworthy comment embeddings**,
  - Comment embedding error
    \[ E_{m,n} \]

- **infer user-aspect reliabilities**
  - User-post reliabilities
    \[ R_{m,n} \]

- **learn word embeddings**
  - Context Error
    \[ Q_{m,n} \]

\[ a_m^* \in \mathbb{R}^D \]
\[ r_n \in \mathbb{R}^K \]
\[ v_\omega \in \mathbb{R}^D \]
Comment Embedding Error

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

\[ E_{m,n} = \|a_m^* - a_{m,n}\|^2 \]

\[ a_{m,n} = [w_{m,n}]^{-1} \sum_{\omega \in w_{m,n}} v_{\omega} \]

user n’s comment on post m
Context Embedding Error

• Learned comment embeddings are similar to the context embedding of the post.

\[ Q_{m,n} = \left| c_m \right|^{-1} \sum_{c \in c_m} \left\| a_{m,n} - v_c \right\|^2 \]

set of words in post m

post word embedding
User-Post Reliability

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

\[ R_{m,n} = \sum_k r_n^{(k)} \cdot (u_n^{(k)} \cdot p_m^{(k)}) \]

- Reliability of aspect k for user n
- Aspect k familiarity for user n
- Aspect k weight for post m
Putting Everything Together

\[
\min_{\{\alpha_m^*, \nu_{\omega}, \{r_n\}} \sum_{n=1}^{N} \sum_{m \in \mathcal{M}_n} R_{m,n} \underbrace{\sum_{n=1}^{N}}_{\text{posts which user n has commented on}} \underbrace{\sum_{m \in \mathcal{M}_n} R_{m,n}}_{\text{user-post reliability}} (\underbrace{E_{m,n}}_{\text{embedding error}} + \beta \odot \underbrace{Q_{m,n}}_{\text{context error}}) \underbrace{\sum_{n=1}^{N} e^{-r_{n}^{(k)}}}_{1; \forall k}
\]
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
- code
- sexual
- corner
- eyesight
- feed
- prefer
- preventing
- vision
- pills
- software
- vacuum
- chamber
- retain
- smoke

(b) Cosmos
- speed
- light
- universe
- mass
- gravity
- time
- question
- black
- space
- earth

(c) Oceanography
- mouth
- legs
- twins
- held
- antimatter
- nose
- arms
- brown
- attack
- alive
Qualitative Study: Word Embedding Similarity

- Word Embedding analysis: encoding trust-aware words

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

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