# Publication Venue Recommendation based on Paper Abstract

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# The Problem

- Given a scientific **paper** $p$
- Recommend an ordered list of “suitable” **publication venues** $v_1, v_2, \ldots, v_N$

# Motivation

- Everyone knows “the” top-level conferences
- Choosing the right venue for early / exploratory work is not easy
- More than 2000 CS conferences
  - Broad spectrum between generalist vs specific
  - How to have high precision and recall ?
- Some emerging proposals
- ...and to be frank: a nice and challenging problem...

# Novelty and Advantages

- Recommendation based solely on **title** and **abstract**
- Unlike earlier proposals based on **full-text** and **reference list**

- May be used **earlier** in the authoring process
- KB much **simpler** to build and maintain

# Our work in a nutshell

- Three approaches
- Assessed on 58000 papers / 300 conferences from Microsoft Academic Search

- Results aligned with existing state of the art
- ...but with much less info from paper and KB !

# Approach 1: Cavnar-Trenkle

Assumption:

- Each venue has a specific **language profile**
  - Profile: n-gram list sorted by frequency ($n \leq 5$)

Recommend:

- Venues with language profiles “closest” to the examined paper

# LDA in a nutshell (I)

INPUT

- Collection of papers
- Predefined #topics

OUTPUT

- Each **topic** is a **mix of words**:
  word vector (prob. of finding that word in “this” topic)
- ...

# Example topics

| Topic | 4 most probable words | | | |
|---|---|---|---|---|
| 1 | data | analysi | mobil | network |
| 2 | system | network | mobil | comput |
| 3 | system | process | analysi | comput |
| 4 | network | sensor | wireless | system |
| 5 | network | data | algorithm | perform |
| 6 | comput | network | servic | perform |

- A topic “**is**” just a word probability vector
- Topics are discovered (generated) **automatically**
- We arbitrarily set #topics=20

# LDA in a nutshell (II)

INPUT

- Collection of papers
- Predefined #topics

OUTPUT

- Each **topic** is a **mix of words**:
  word vector (element *k* = prob. of being found in topic *k*)
- Each **paper** is a **mix of topics**
  topic vector (element *k* = prob. of being related to topic *k*)

# Approach 2: 2-Step LDA

Assumption:

- Each venue has a **prevalent topic**
  - The one most probable for most papers
- **Sub**-topics are the topics generated with LDA **restricted** to venues with **the same prevalent topic**

Recommend:

- Venues with prevalent topic and sub-topics “closest” to the examined paper

# Approach 3: LDA+Clustering

Assumption:

- Papers may be **clustered** based on their topic mix
- **Sub**-topics are the topics generated with LDA **restricted** to papers from **the same** ~~prevalent topic~~ **cluster**

Recommend:

- Venues with subtopic mix “closest” to the examined paper

# Experimental Evaluation

- 58000 papers / 300 conferences
  from Microsoft Academic Search

- Half training (Knowledge Base)
- Half testing (Recommend)
  - “Half” = same #papers in each conference

- Two repetitions (with different splitting)

# Metric

- Venue-Accuracy@N
  - Prediction is correct when:
    real venue is in the N recommended venues
- Probably excessively (and unnecessarily) severe
  - A paper may fit many conferences

# Baseline

- Random recommender

- Earlier proposals: not really meaningful
  - Very different datasets
    (size, content)
  - Keep in mind: they need **full text** and **reference list**

# Venue-Accuracy@N

| Method | venue-acc.@$N$ (%) $N=3$ | $N=5$ | $N=10$ | Dataset $\lvert A \rvert$ | $\lvert V \rvert$ |
|---|---|---|---|---|---|
| Cavnar-Trenkle | 26.8 | 34.0 | 45.6 | | |
| | | | | 58466 | 300 |
| Random recommender | 1.0 | 1.7 | 3.3 | | |
| [2] ACM | | | | | |
| [2] CiteSeer | | | | | |
| [3] | | | | | |
| [4] | | | | | |

- Simple n-gram profile is indeed effective

# Venue-Accuracy@N

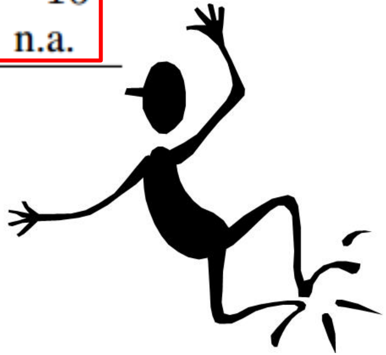
| Method | venue-acc.@$N$ (%) $N=3$ | $N=5$ | $N=10$ | Dataset $\|A\|$ | $\|V\|$ |
|---|---|---|---|---|---|
| Cavnar-Trenkle | 26.8 | 34.0 | 45.6 | 58466 | 300 |
| Two-step-LDA | 3.4 | 3.8 | 4.0 | | |
| LDA+clustering | 16.1 | 21.7 | 33.2 | | |
| Random recommender | 1.0 | 1.7 | 3.3 | | |
| [2] ACM | | | | | |
| [2] CiteSeer | | | | | |
| [3] | | | | | |
| [4] | | | | | |

- Topic models may *(or may not)* be effective
- Many matching criteria

# Earlier proposals

| Method | venue-acc.@$N$ (%) $N=3$ | $N=5$ | $N=10$ | Dataset $\|A\|$ | $\|V\|$ |
|---|---|---|---|---|---|
| Cavnar-Trenkle | 26.8 | 34.0 | 45.6 | 58466 | 300 |
| Two-step-LDA | 3.4 | 3.8 | 4.0 | | |
| LDA+clustering | 16.1 | 21.7 | 33.2 | | |
| Random recommender | 1.0 | 1.7 | 3.3 | | |
| [2] ACM | - | 55.7 | 69.8 | 172 890 | 2197 |
| [2] CiteSeer | - | 23.9 | 29.0 | 35 020 | 739 |
| [3] | 91.6 | - | - | 960 | 16 |
| [4] | - | - | 63.2 | 295 317 | n.a. |

- Relying on **only title and abstract** seem to be enough !



# A Weaker Metric

- **Subdomain-**Accuracy@N
    - Each venue has one or more of 24 subdomains (assigned by Microsoft Academic Search)

    - Prediction is correct when:

      subdomains of real venue and of N recommended venues have non-empty intersection

# Subdomain-Accuracy@N

| Method | sub-domain-acc.@$N$ (%) $N=3$ | $N=5$ | $N=10$ |
|---|---|---|---|
| Cavnar-Trenkle | 54.1 | 61.1 | 70.9 |
| Two-step-LDA | 9.9 | 10.1 | 10.2 |
| LDA+clustering | 47.3 | 56.5 | 68.9 |
| Random recommender | 14.3 | 22.6 | 40.1 |

- “Similar” conclusions

# Thanks for your attention

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