A Framework for Optimizing Paper Matching
Laurent Charlin, Richard Zemel and Craig Boutilier

**Problem:** Assign submitted papers to reviewers

Standard solutions have limitations:
- Completely centralized or de-centralized
- Bidding

Some recent work using CF + matching

**We propose** a flexible framework for matching reviewers to papers:
- **Predict** missing suitabilities (ratings)
- **Find optimal** matchings

### Matching

Possible desiderata:
- Match papers to best reviewers
- Load constraints

\[
\begin{align*}
&\text{max. } J^{\text{basic}}(x) = \sum_r \sum_p s_{rp} x_{rp} \\
&\text{s.t. } x_{rp} \in \{0, 1\}, \forall r, p \\
&\sum_r x_{rp} = R_{\text{targ}}, \forall p \\
&\sum_p x_{rp} \geq P_{\text{min}}, \sum_p x_{rp} \leq P_{\text{max}}, \forall r.
\end{align*}
\]

- **Load equity**

\[
J^{\text{balance}}(x) = J^{\text{basic}} + \sum_r \lambda f\left(\sum_p x_{rp} - \bar{x}\right)
\]

- **Conflicts of interest**
- **Non-linear relationship between utilities**

### Learning Methods

**LR** - Linear regression using words from submitted papers

**BPMF** - Bayesian probabilistic matrix factorization
- Factorizes the suitability matrix
- Collaborative filtering

**LM** - Language model
- Model reviewers using a word-level model

### Experiments

- Data from NIPS’09 and NIPS’10
  - Use top 1,000 words
  - N10: 1250 papers, 48 revs
    - avg. 143 suitabilities per reviewer
    - mean suitability 1.14
  - N09: 1079 papers, 30 revs
    - mean suitability 0.19

### Conclusion:
Effective for determining high-quality matches using few suitabilities

**Current work:** Active learning approaches

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**Our contributions:**
- Compare learning methods
- Incorporate objectives and constraints
- Interaction between learning & matching
  - **Aim:** make learning sensitive to final objective

**Learning Predictions**
- RMSE objective
- LR does the best
- Information contained in papers is useful

**Matching Performances**
- Absolute matching performance

- Better performance when learning with transformed objective
- LM does well at the beg.

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