Fair Online Dating Recommendations for Sexually Fluid Users via Leveraging Opposite Gender Interaction Ratio

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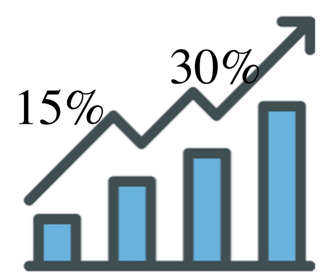
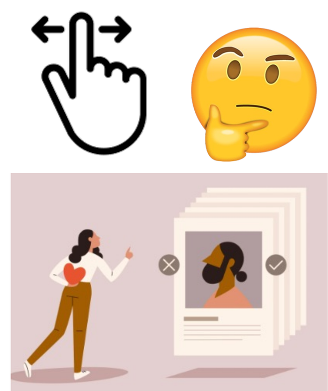
Motivation

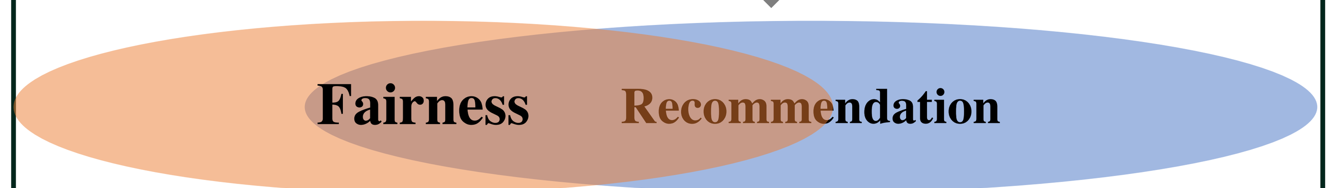
Online dating platforms
Increasing popularity





- Information overload
- Unawareness

Online dating recommender systems



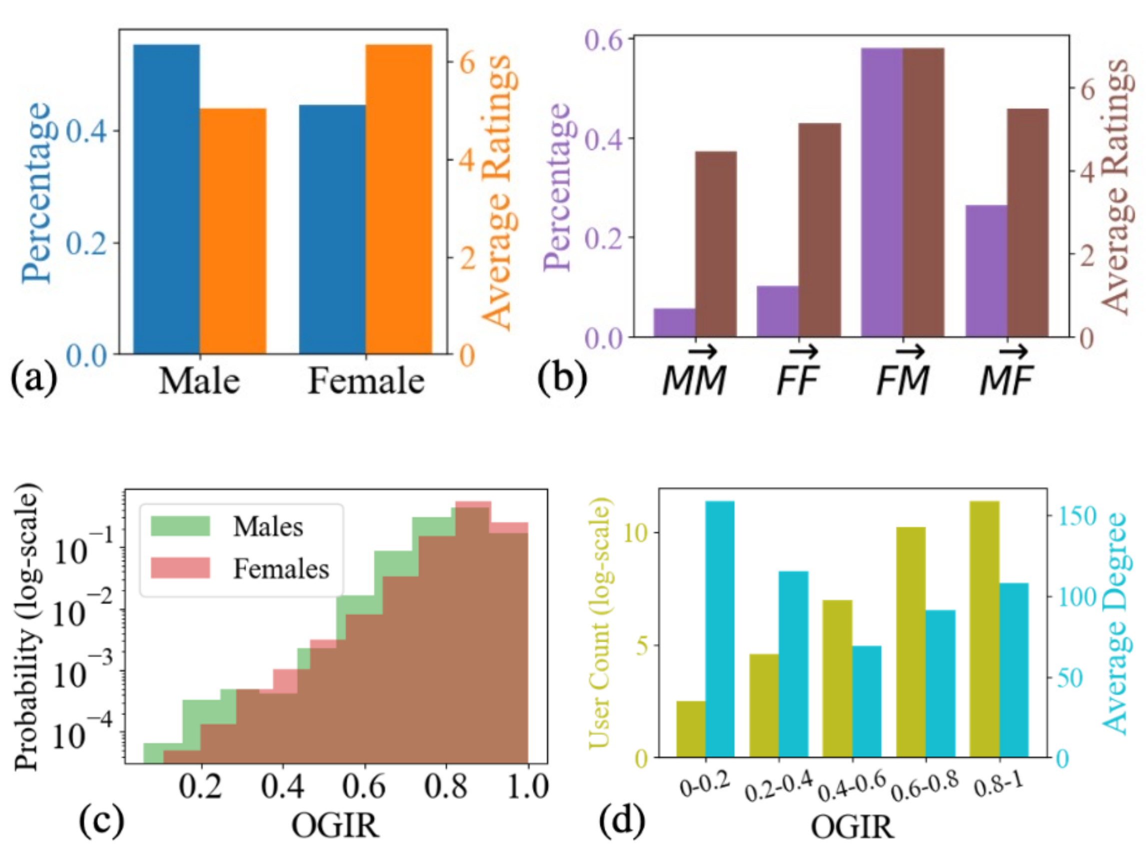
Whether different groups of users can be treated similarly?

- Gender
- Race
- Religion
- Interaction number
- Purchase amount

Sexual Orientation

Real-World Dataset Analysis

Czech Republic Dating Network → User interactions, Gender identity



Complex user behavior
Prefer/ignore the opposite gender at varied levels

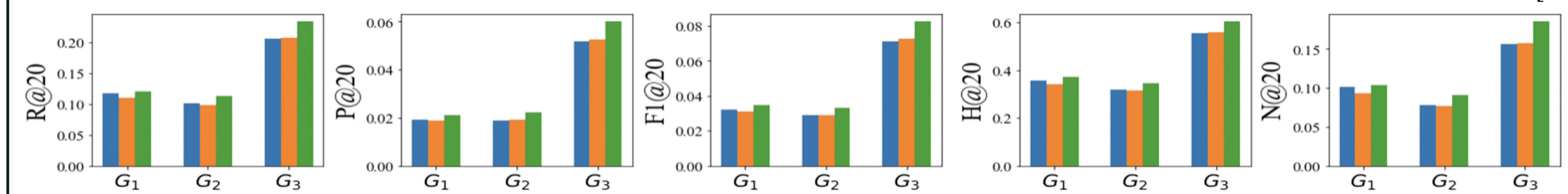
OGIR: opposite gender interaction ratio (indicator of sexual orientation)

Fairness Concerns

Whether user groups with various sexual orientations can be treated fairly?

Investigating recommendation quality based on the indicator of sexual orientation (OGIR)

u in G_1, G_2, G_3 if OGIR(u) in $\left[0,\frac{1}{3}\right), \left[\frac{1}{3},\frac{2}{3}\right), \left[\frac{2}{3},1\right]$



Recommendation Algorithms

Fairness metric

$$\Delta_X(\mathcal{G}) = \frac{\mathbb{E}_{(G_1,G_2)\in\mathcal{G}\times\mathcal{G}}|Q_X(G_1) - Q_X(G_2)|}{Q_X^{ave}} \qquad Q_X^{ave} = \frac{\sum_{G\in\mathcal{G}} Q_X(G)}{|\mathcal{G}|}$$

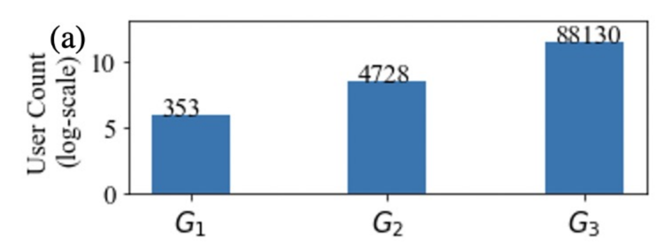
Qx: recommendation quality on metric x

Source of Bias & Bias Mitigation

What is the source of group performance gap? How to mitigate the bias?

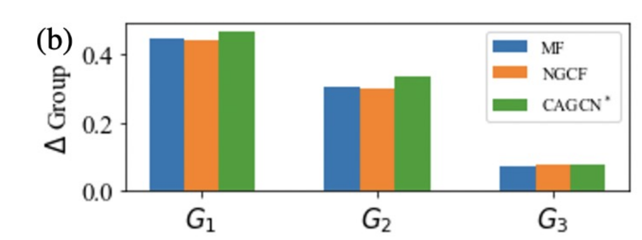
Investigating source of bias and proposing corresponding mitigation strategies

Group data imbalance: re-weighting



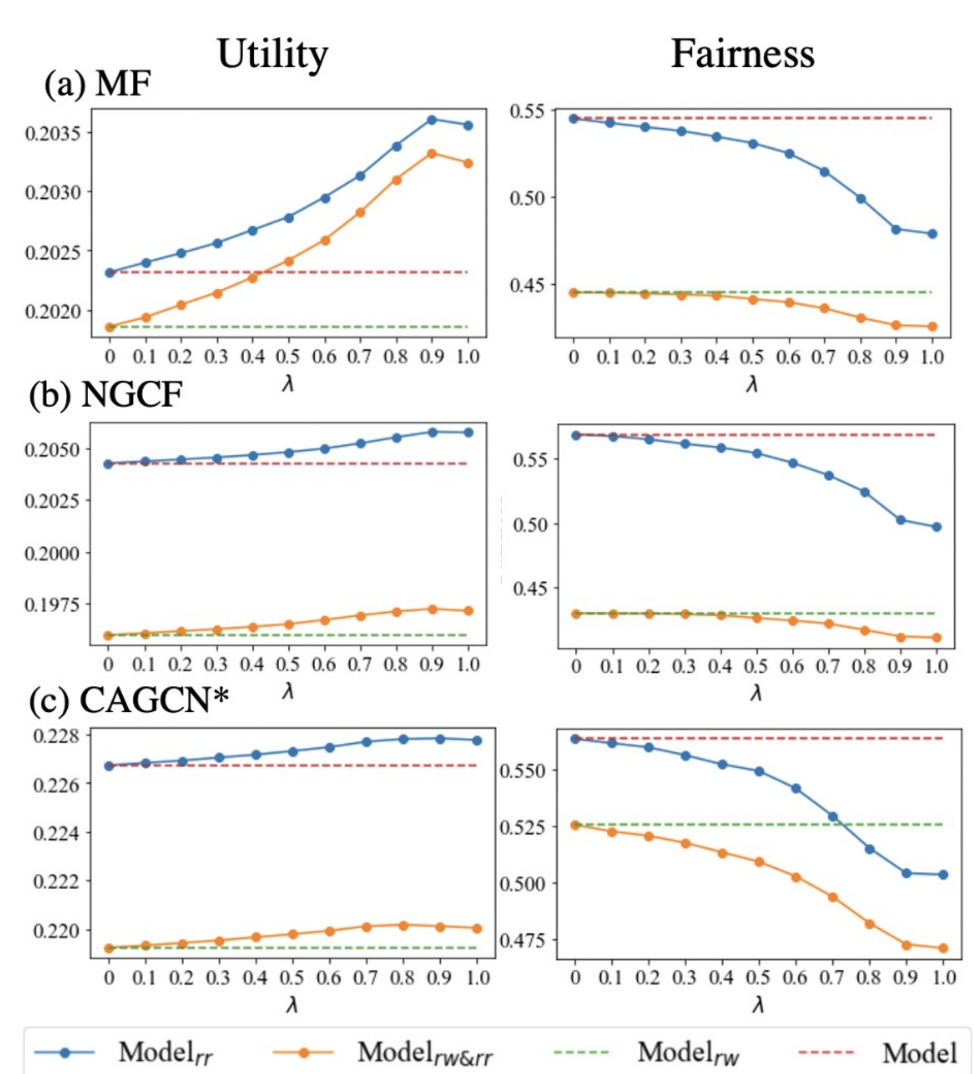
$$\mathcal{L}_{\text{BPR}}^{\text{re-weighting}} = -\sum_{(u,i,j)\in\mathcal{D}} w_{G(u)} \log\sigma(\hat{y}_{ui} - \hat{y}_{uj}) + \lambda_\Theta\|\Theta\|^2$$

Group calibration imbalance: re-ranking

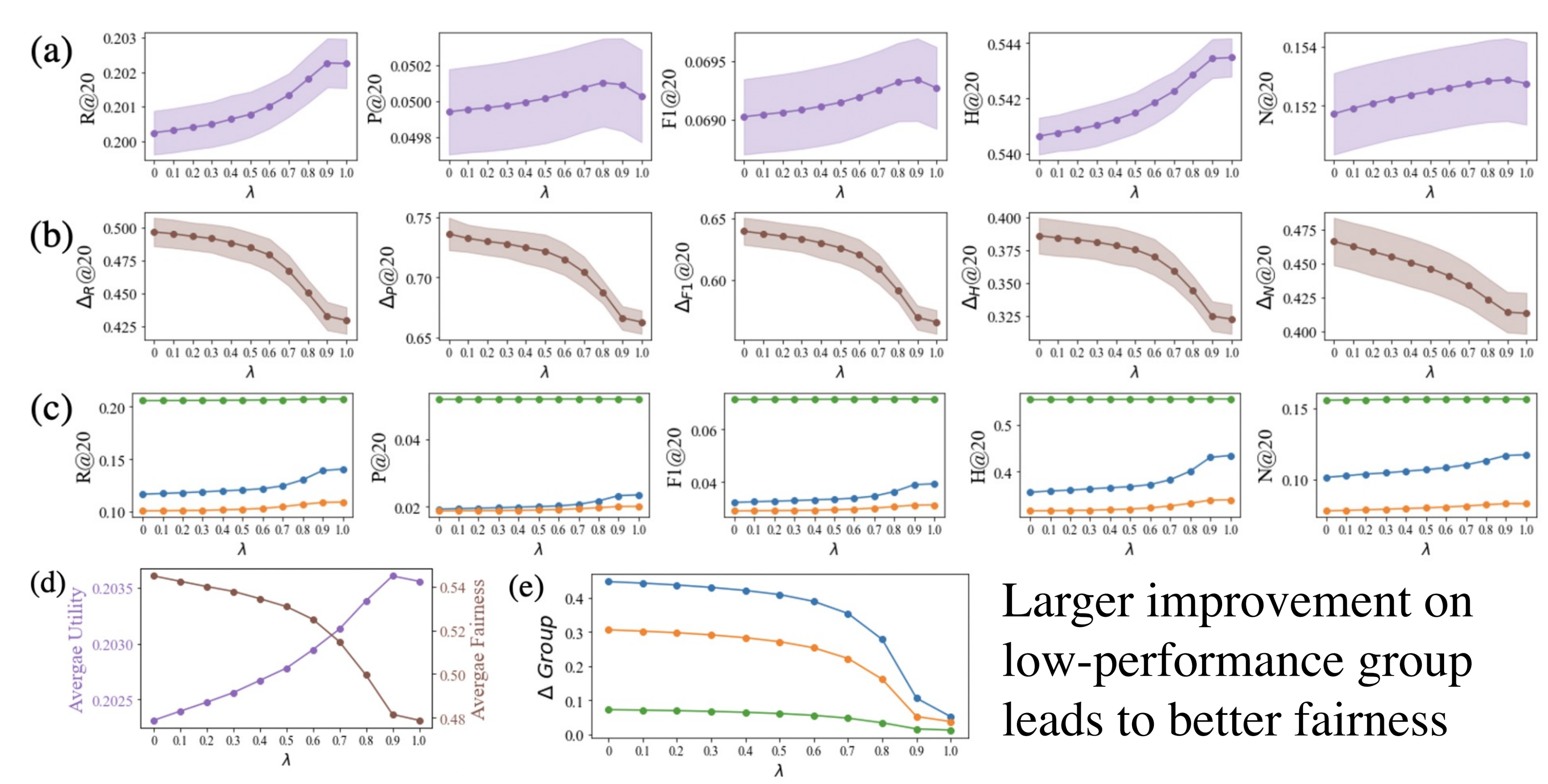


$$\mathcal{R}_u^* = {}_{\mathcal{R}_u, |\mathcal{R}_u|=\text{K}} \ (1-\lambda)S(\mathcal{R}_u) - \lambda\Delta_{\text{User}}(u, \mathcal{R}_u)$$

Experiments



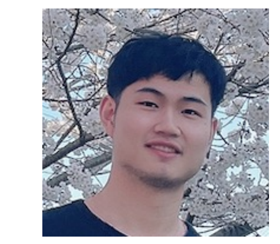
- Both re-weighting and re-ranking improve fairness
- The combined method leads to the best performance



Larger improvement on low-performance group leads to better fairness

Acknowledgement

Collaborators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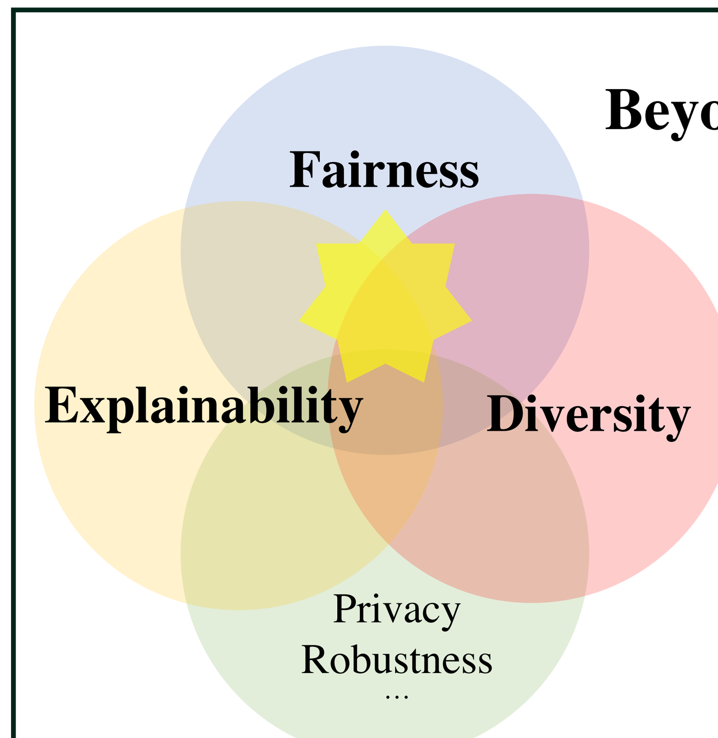
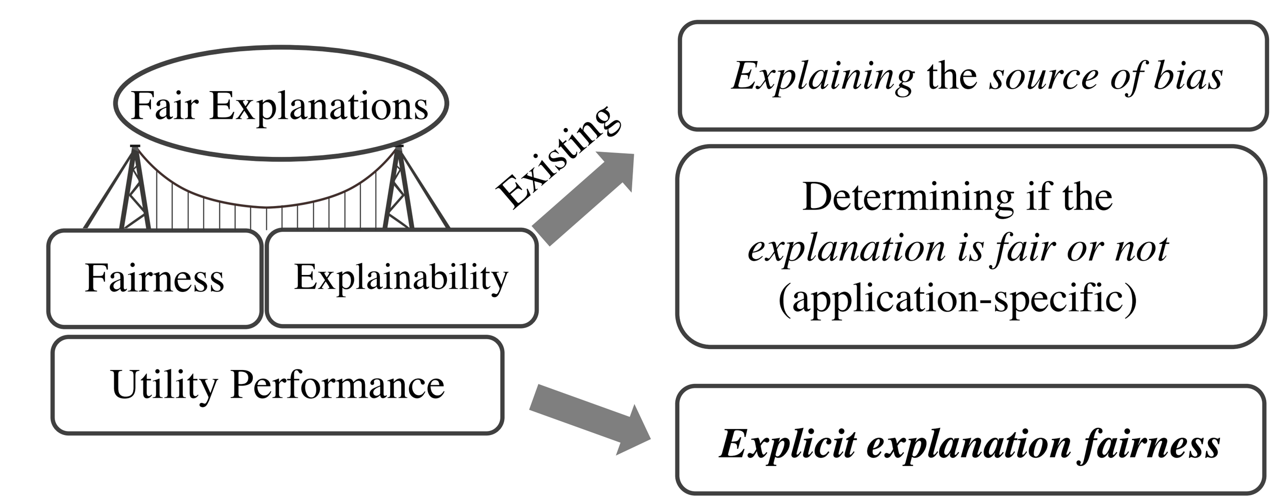
KDD STA
Student Travel Award

Other works

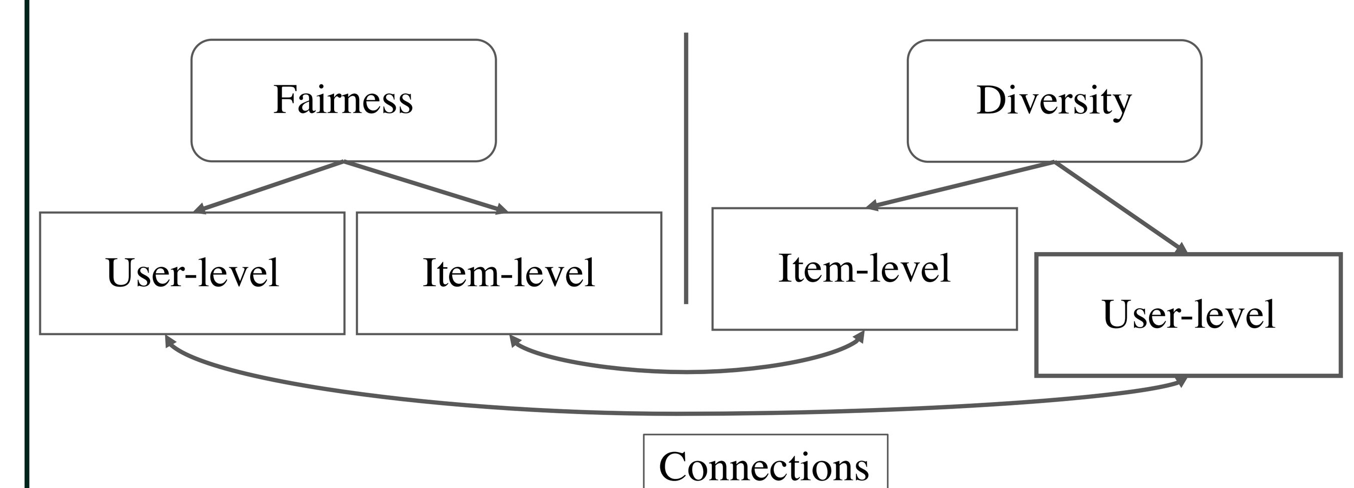


Beyond-utility perspectives Responsible AI

Welcome to my website for code and more details



Fairness and Explainability: Bridging the Gap Towards Fair Model Explanations (AAAI'23)



Fairness and Diversity in Recommender Systems: A Survey (in submission, available on arxiv)