# Story

Preference learning is useful for problems such as finding convincing arguments, where it is hard to give a score to a single document in isolation. Another example is finding a solution to question x; or choosing the best summary of a piece of text; or the best graph fit to some data.

In a large dataset, we cannot get enough pairs to label all items. Instead, we learn to generalise from the items’ features.

There are several ways to do preference learning that generalises beyond seen pairs and uses the structure in the features. GPPL has a number of advantages of using state-of-the-art nonparametric Bayesian model. Neural networks are an alternative but not yet tested on this problem – a likely drawback is the need for lots of training data before they can work well.

The problem with GPPL to date is that it was proposed with an inefficient MAP approximation, which may also give poorer results. Recent work on SVI shows how we can overcome this to scale to much larger datasets than were previously possible.

We present our SVI method.

(The alternative to using our method is to alter the likelihood model of the Hensman approach. It’s unclear why this would be better. See the difference between the factorised and other models… Also, they do not show how to do this for preference learning, nor do they test it for this task).

Experiments should show how well SVI works with GPPL…

…And which settings work particularly well on example applications.

*Novelty compared to TACL paper:*

* *we explain the methodology in detail showing how it was developed and why*
* *evaluate how SVI parameters affect convergence*
* *advantage of submitting now is that the two papers can be different enough, yet don’t require explicit comparison of novelty – make sure that key results from TACL paper are not spoilt?*

Experiments:

* Real data with argumentation.
* Small subset to compare SVI / VB:
  + Show how M affects quality of final solution. Plot with single line/points only. X-axis shows M, y-axis shows log marginal likelihood or AUC?
  + Show how P\_n affects time needed to converge. Plot with different lines for different P\_n. x-axis = no. iterations, y-axis = log marginal likelihood or AUC?
* Is this necessary? Another large PL dataset, ideally from a different domain and with metrics for other rival methods.

# Inferring the Ground Truth from Multiple Workers

Adding in a common mean to infer ground truth:

* Advantage: if we were to take a latent component as true instead, it is unclear how to set priors so that the common gold pattern is chosen for that feature.
* Is there a switch to turn off the spammers? In MACE, IBCC, we learn that spammers are random/always choose one label. Here we can learn either very high noise s\_k for worker k, or a factor that is (1 – mean) + f\_spammer.

One form of noise that is not well covered is in the labels themselves: the worker could click the left-hand button all the time, which would be detected using IBCC/MACE. In GPPL it would manifest eventually as high s\_k noise. Coupling the models together might help catch this noise earlier.

# To-Do list for Paper D:

1. Change style to IJCAI? IJCAI 2017 had a page limit of 6 pages for the main text + 1 for references. Deadline is around February. AAAI is 8th September abstract and 11th paper; 7 pages main text + 1 references.
2. Create new ML paper \*[Paper D] Scalable GP Preference Learning\* outline. This can combine with technical bits from the personalised argumentation paper; also take on the crowdsourcing angle --> using the collaborative model to de-noise the crowdsourced data. May also need some scalability plots to show convergence.