# Multilingual Anchoring: Interactive Topic Modeling and Alignment across Languages

**Michelle Yuan**[1] Benjamin Van Durme[2] Jordan Boyd-Graber[1]

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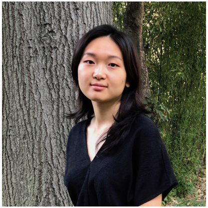
# Authors

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- Analysts need to examine multilingual text collections, but are scarce in one or more languages.

# Modeling Multilingual Topics

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crop, corn, wheat,
tractor, cows,
農業 (nóngyè),
牲畜 (shēngchù),
米 (mǐ),
收成 (shōuchéng)

environment,
earth, energy,
recycling, trash,
碳足跡 (tàn zújì),
太陽能 (tàiyángnéng)
污染 (wūrǎn),
空氣 (kōngqì)

economy, cash,
industry, income,
services, demand,
經濟 (jīngjì),
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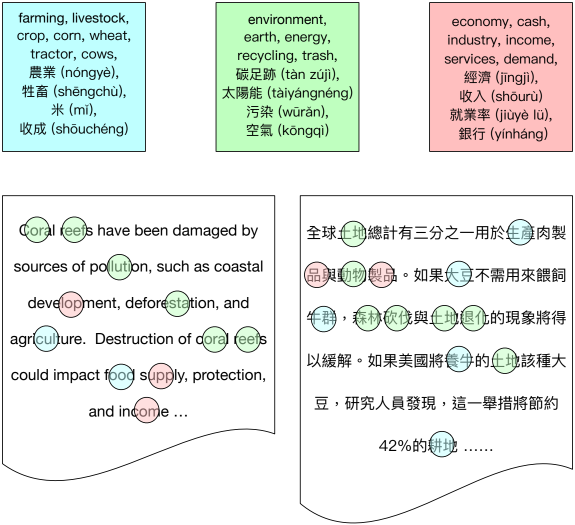

# Generative Approaches

- Polylingual Topic Model (Mimno et al., 2009)
- JointLDA (Jagarlamudi and Daumé, 2010)
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**These methods are slow, assume extensive knowledge about languages, and preclude human refinement.**

# Anchor words

### Definition

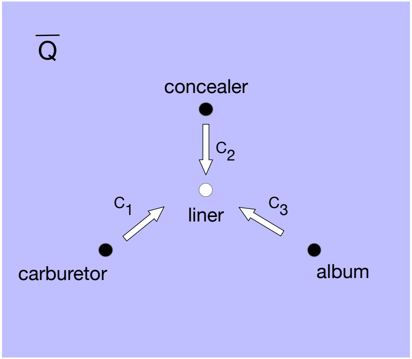
An **anchor word** is a word that appears with *high* probability in one topic but with *low* probability in all other topics.

# From Co-occurrence to Topics

- Normally, we want to find $p(\text{word} \mid \text{topic})$ (Blei et al., 2003).
- Instead, what if we can easily find $p(\text{word} \mid \text{topic})$ through using anchor words and conditional word co-occurrence $p(\text{word 2} \mid \text{word 1})$?

# From Co-occurrence to Topics

$$\bar{Q}_{i,j} = p(w_2 = j \mid w_1 = i)$$



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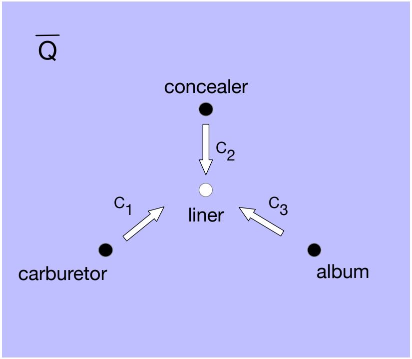


$$\bar{Q}_{\text{liner}} \approx C_1 \bar{Q}_{\text{carburetor}} + C_2 \bar{Q}_{\text{concealer}} + C_3 \bar{Q}_{\text{album}}$$

$$= 0.4 * \begin{bmatrix} 0.3 \\ \cdots \\ 0.1 \end{bmatrix} + 0.2 * \begin{bmatrix} 0.1 \\ \cdots \\ 0.2 \end{bmatrix} + 0.4 * \begin{bmatrix} 0.1 \\ \cdots \\ 0.4 \end{bmatrix}$$

# Anchoring

- If an anchor word appears in a document, then its corresponding topic is among the set of topics used to generate document (Arora et al., 2012).
- Anchoring algorithm uses word co-occurrence to find anchors and gradient-based inference to recover topic-word distribution (Arora et al., 2013).
- Runtime is **fast** because algorithm scales with number of unique word types, rather than number of documents or tokens.

# Anchoring

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$$\bar{Q}_i \approx \sum_{k=1}^{K} C_{i,k} \bar{Q}_{s_k} \text{ subject to } \sum_{k=1}^{K} C_{i,k} = 1 \text{ and } C_{i,k} \geq 0.$$

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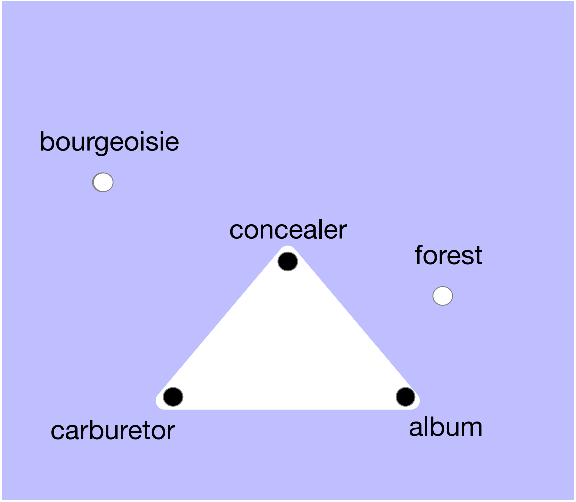
3. Find topic-word matrix:

$$\begin{aligned} A_{i,k} &= p(w = i \mid z = k) \propto p(z = k \mid w = i) p(w = i) \\ &= C_{i,k} \sum_{j=1}^{V} \bar{Q}_{i,j}. \end{aligned}$$

# Finding Anchor Words

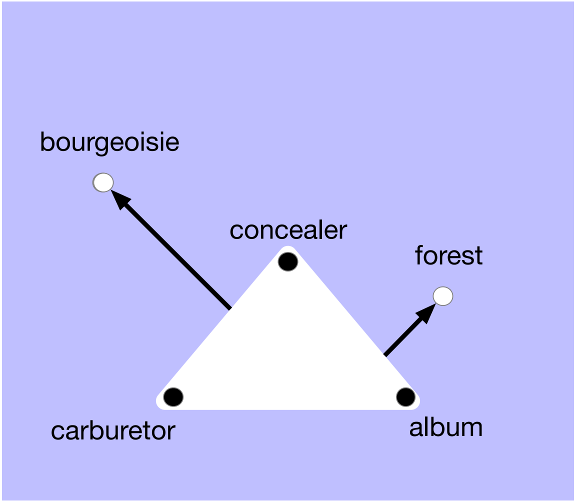
- So far, we assume that anchor words are given.
- How do we find anchor words from documents?

# Finding Anchor Words




Anchor words are the vertices of the co-occurrence convex hull.

# Finding Anchor Words

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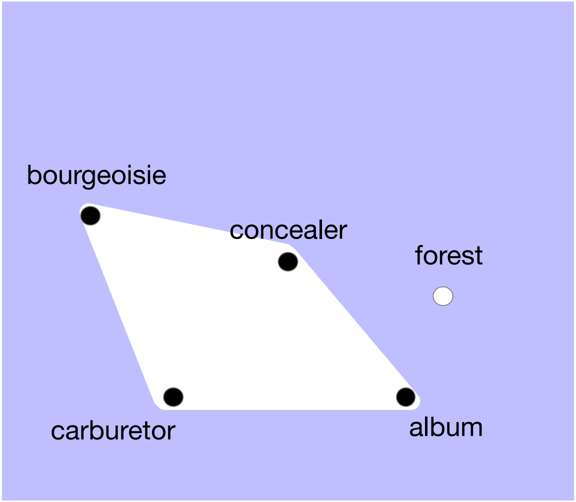


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# Issues with Topic Models

| Topics |
| --- |
| music concert singer voice chorus songs album |
| singer pop songs music album chorale jazz |
| cosmetics makeup eyeliner lipstick foundation primer eyeshadow |

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**Duplicate topics.**

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**Ambiguous topics.**
**Overly-specific topics.**

# Interactive Anchoring

- Incorporating interactivity in topic modeling has shown to improve quality of model (Hu et al., 2014a).
- Anchoring algorithm offers speed for interactive work, but single anchors are unintuitive to users.
- **Ankura** is an interactive topic modeling system that allows users to choose multiple anchors for each topic (Lund et al., 2017).
- After receiving human feedback, **Ankura** only takes a few seconds to update topic model.

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**These methods only work for monolingual document collections.**

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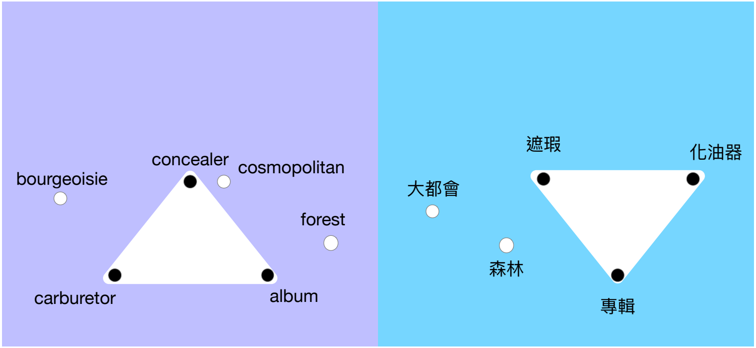
**Idea:** If dictionary $\mathcal{B}$ contains entry $(w, v)$, create a link between $w$ and $v$.

# Finding Multilingual Anchors



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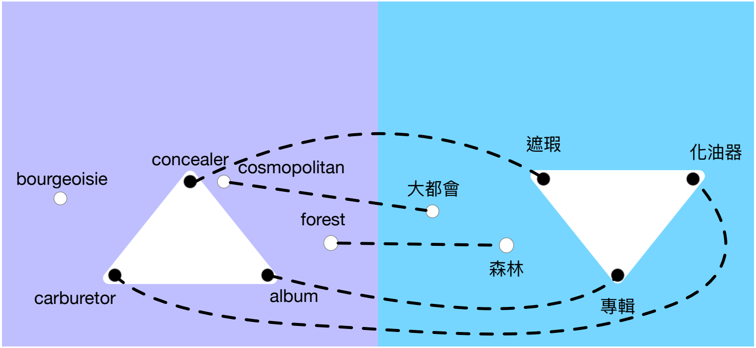
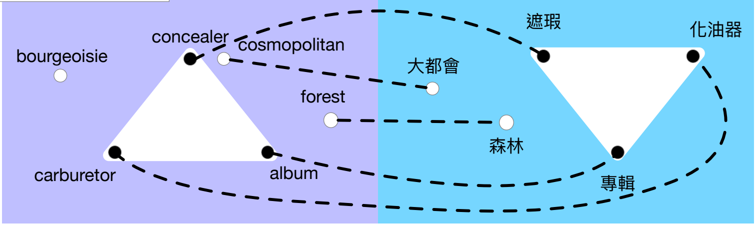


# Finding Multilingual Anchors

Bourgeoisie does not have a Chinese translation, so it cannot be picked as an anchor word even if it is the farthest word from the convex hull.



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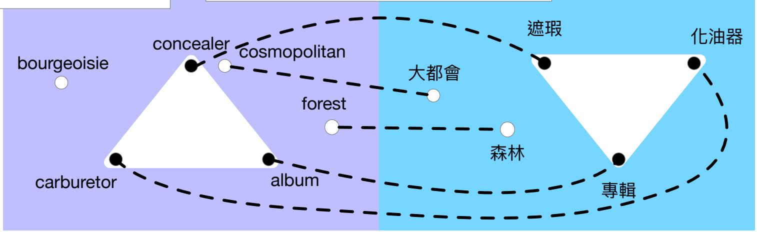

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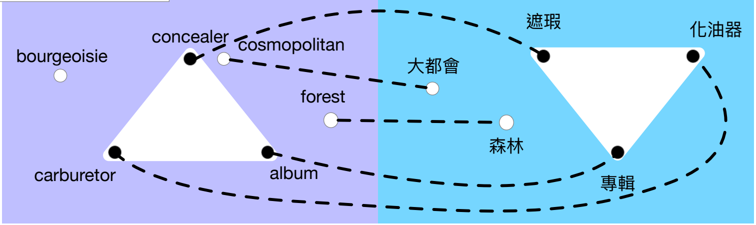
Forest and its translation 森林 (sēnlín) are not the furthest points from their respective convex hull, but neither are too close. So, they are chosen as the next anchor words.



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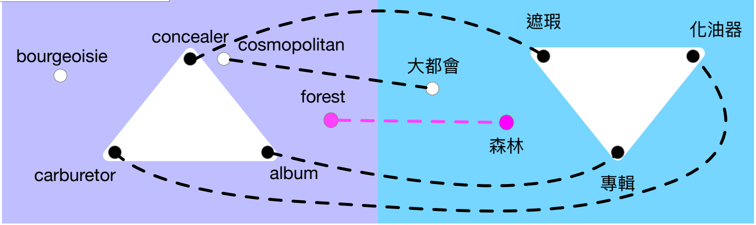

# Multilingual Anchoring

1. Given a dictionary, create links between words that are translations of each other.
2. Select an anchor word for each language such that the words are linked and span of anchor words is maximized.
3. Once anchor words are found, separately find topic-word distributions for each language.

- What if dictionary entries are scarce or inaccurate?
- What if topics aren't aligned properly across languages?

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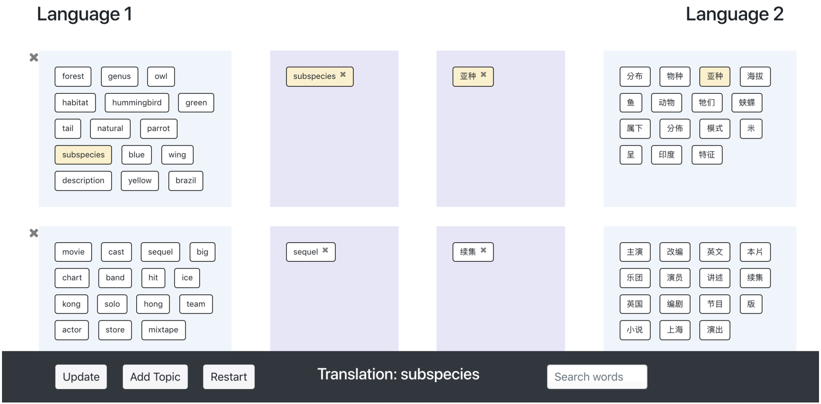
**Incorporate human-in-the-loop topic modeling tools.**

# MTAnchor



Language 1
Language 2
forest
genus
owl
habitat
hummingbird
green
tail
natural
parrot
subspecies
blue
wing
description
yellow
brazil
subspecies
亚种
分布
物种
亚种
海拔
鱼
动物
牠们
蛱蝶
属下
分佈
模式
米
呈
印度
特征
movie
cast
sequel
big
chart
band
hit
ice
kong
solo
hong
team
actor
store
mixtape
sequel
续集
主演
改编
英文
本片
乐团
演员
讲述
续集
英国
编剧
节目
版
小说
上海
演出
Update
Add Topic
Restart
Translation: subspecies
Search words

# Experiments

**Datasets:**

1. Wikipedia articles (EN, ZH)
2. Amazon reviews (EN, ZH)
3. LORELEI documents (EN, SI)

# Experiments

**Metrics:**

1. Classification accuracy
   - Intra-lingual: train topic model on documents in one language and test on other documents in the *same* languages
   - Cross-lingual: train topic model on documents in one language and test on other documents in a *different* language.
2. Topic coherence (Lau et al., 2014).
   - Intrinsic: use the trained documents as the reference corpus to measure local interpretability.
   - Extrinsic: use a large dataset (i.e. entire Wikipedia) as the reference corpus to measure global interpretability.

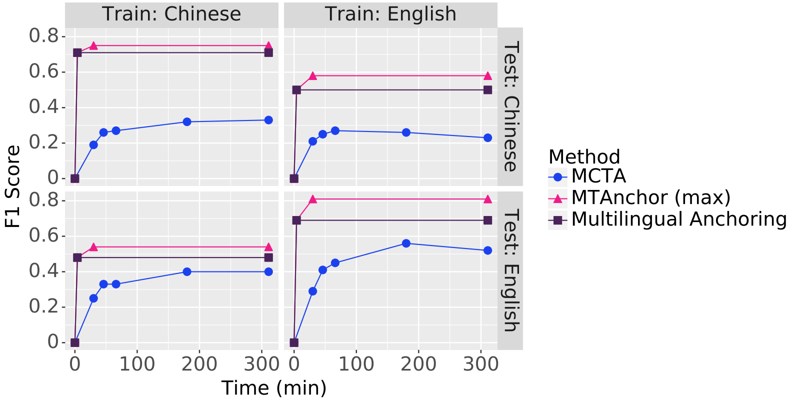
# Comparing Models

| Dataset | Method | Classification accuracy EN-I | ZH-I SI-I | EN-C | ZH-C SI-C |
|---|---|---|---|---|---|
| Wikipedia | Multilingual anchoring | 69.5% | 71.2% | 50.4% | 47.8% |
| | MTAnchor (maximum) | **80.7%** | **75.3%** | **57.6%** | **54.5%** |
| | MTAnchor (median) | 69.5% | 71.4% | 50.3% | 47.2% |
| | MCTA | 51.6% | 33.4% | 23.2% | 39.8% |
| Amazon | Multilingual anchoring | **59.8%** | **61.1%** | **51.7%** | **53.2%** |
| | MCTA | 49.5% | 50.6% | 50.3% | 49.5% |
| LORELEI | Multilingual anchoring | **20.8%** | **32.7%** | **24.5%** | **24.7%** |
| | MCTA | 13.0% | 26.5% | 4.1% | 15.6% |

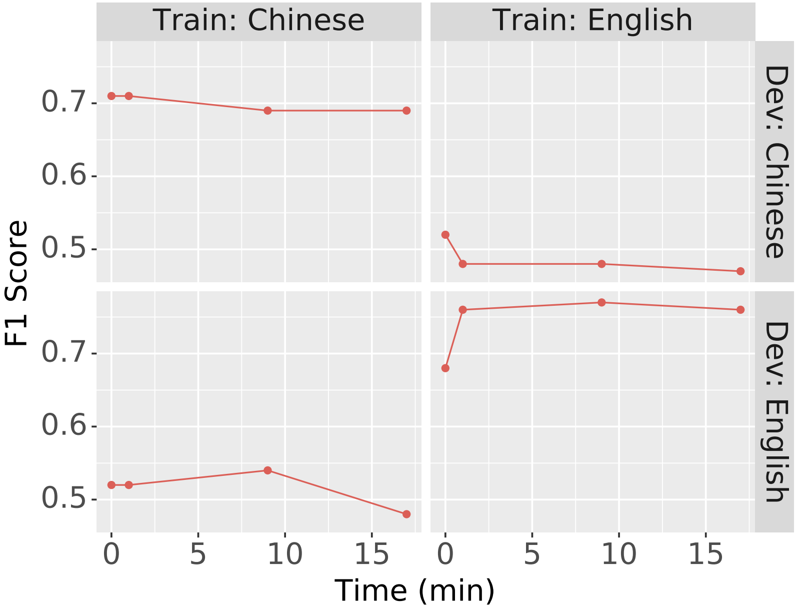
# Comparing Models

| | | Topic coherence | | | |
|---|---|---|---|---|---|
| Dataset | Method | EN-I | ZH-I SI-I | EN-E | ZH-E SI-E |
| Wikipedia | Multilingual anchoring | 0.14 | 0.18 | 0.08 | 0.13 |
| | MTAnchor (maximum) | **0.20** | **0.20** | **0.10** | **0.15** |
| | MTAnchor (median) | 0.14 | 0.18 | 0.08 | 0.13 |
| | MCTA | 0.13 | 0.09 | 0.00 | 0.04 |
| Amazon | Multilingual anchoring | **0.07** | **0.06** | **0.03** | **0.05** |
| | MCTA | -0.03 | 0.02 | 0.02 | 0.01 |
| LORELEI | Multilingual anchoring | 0.08 | 0.00 | 0.03 | n/a |
| | MCTA | **0.13** | 0.00 | **0.04** | n/a |

# Multilingual Anchoring Is Much Faster



# Improving Topics Through Interactivity



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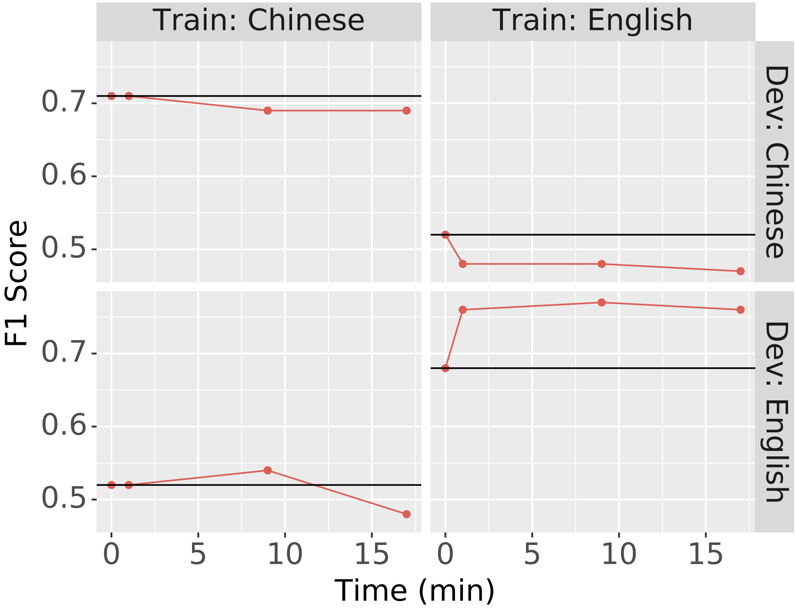

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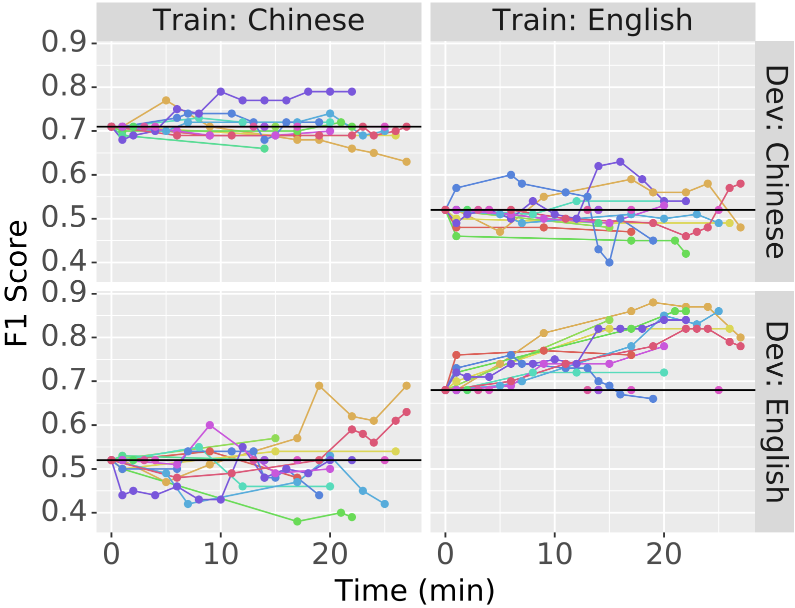

# Comparing Topics

| Dataset | Method | Topic |
|---|---|---|
| Wikipedia | MCTA | dog san movie mexican fighter novel california |
| | Multilingual anchoring | **adventure** daughter bob kong hong robert movie |
| | MTAnchor | **kong hong movie** office martial box reception |
| Amazon | MCTA | woman food eat person baby god chapter |
| | Multilingual anchoring | eat diet food recipe **healthy** lose weight |
| LORELEI | MCTA | help need floodrelief please families needed victim |
| | Multilingual anchoring | aranayake warning landslide site missing nbro areas |

# Why Not Use Deep Learning?

- Neural networks are data-hungry and unsuitable for low-resource languages
- Deep learning models take long amounts of time to train
- Pathologies of neural models make interpretation difficult (Feng et al., 2018)

# Summary

- Anchoring algorithm can be applied in multilingual settings.
- People can provide helpful linguistic or cultural knowledge to construct better multilingual topic models.

# Future Work

- Apply human-in-the-loop algorithms to other tasks in NLP.
- Better understand the effect of human feedback on cross-lingual representation learning.

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