Fuzzy D'Hondt's Algorithm for On-line Recommendations Aggregation

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Task, Motivation

- **Fair (proportional) representation of multiple recommending algorithms based on their on-line performance**
  - Aggregate multiple lists of recommended items R_i corresponding to the recommending strategy rs_i into a single list of items R based on the current performance of rs_i

- **Why?**
  - Multiple recommending strategies may be both ***relevant*** (up to some extent) and ***highly diverse***
  - Multiple strategies can be used to model ***various user's interests***, which should be present in recommendations [Steck 2018]

⇨ Fair aggregation of multiple base recommenders may provide relevant, yet highly diverse recommendations or cover multiple users interests

[Steck 2018] Harald Steck, Calibrated recommendations. RecSys 2018

Motivating Example: Assembling Police Photo Lineups

Recommend candidates similar to the suspect, so the lineup is unbiased

- Two strategies: CB attribute-based & visual-based (DCNN)

Results:

- Visual RS is better *(58% vs 37% of selections, not so good for rare ethnics)*
- However, very small candidates intersection *(1.8% for top-20 candidates)*
  - ⇨ CB strategy was relevant up to some extent
  - ⇨ CB proposed some relevant candidates which Visual could not
  - ⇨ *Both strategies should be present in final recommendations*
  - ⇨ *Simple weighted aggregation would over-sample visual strategy*
  - ⇨ *Thompson sampling MAB* [Broden 2018] *would probably over-sample best method as well*

What about something that is tailored to preserve fair distribution?

Biased lineup, *floridainnocence.org*

(Fairly) unbiased lineup

[Broden 2018] Bjorn Broden et al. Ensemble recommendations via thompson sampling: An experimental study within e-commerce. IUI 2018

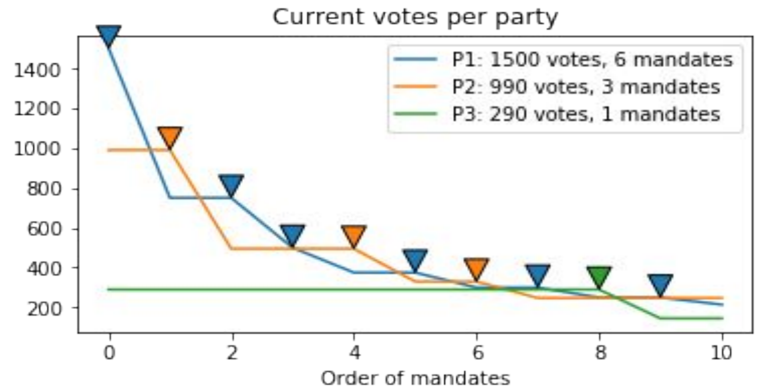
D’Hondts Election Algorithm

- *What about something that is tailored to preserve fairness?*
- Range of algorithms designed to convert votes to mandates in public elections
  - D’Hondt’s election algorithm [D’Hondt 1882]
    - One of the widest-used method in proportional election systems (e.g., 23 countries from Europe, including Denmark)
    - Core principle:
      - Party with the most current votes v_{curr} wins the next candidate, the best candidate of the winning party is selected
      - Upon a selection of a candidate (k-th from this party), the volume of party’s current votes is reduced $v_{curr} = \frac{v_{orig}}{k+1}$

⇨ *Algorithm outputs an ordered list of „current best“ candidates*

⇨ *Volume of per-party votes corresponds with the volume of per-party candidates*

⇨ *Minimize the level of over-representation of the most over-represented party*



[D’Hondt 1882] Victor D’Hondt, Systeme pratique et raisonne de representation proportionnelle. C.Muquardt, 1882

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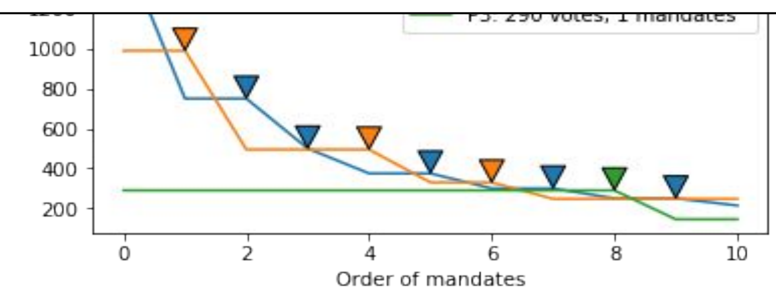
Can be considered as parallel hybridization algorithm



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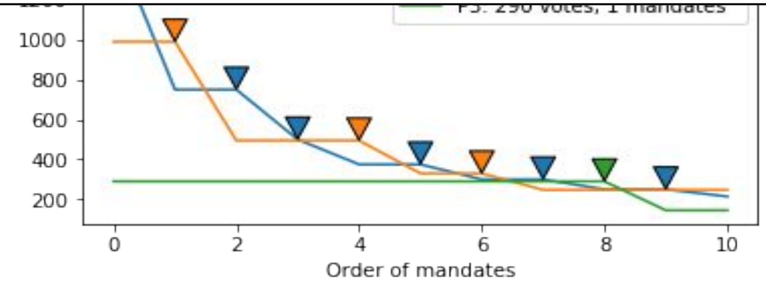
Are RS aggregations and Elections the same problem?



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D'Hondts Election Algorithm - Limitations

- Politics:
  - *Can a person join multiple parties simultaneously?*

NOPE

- Recommender systems:
  - *Can be an item recommended by multiple RS strategies?*

Sure, why not

  - *What about some bonus for items recommended by multiple RS?*

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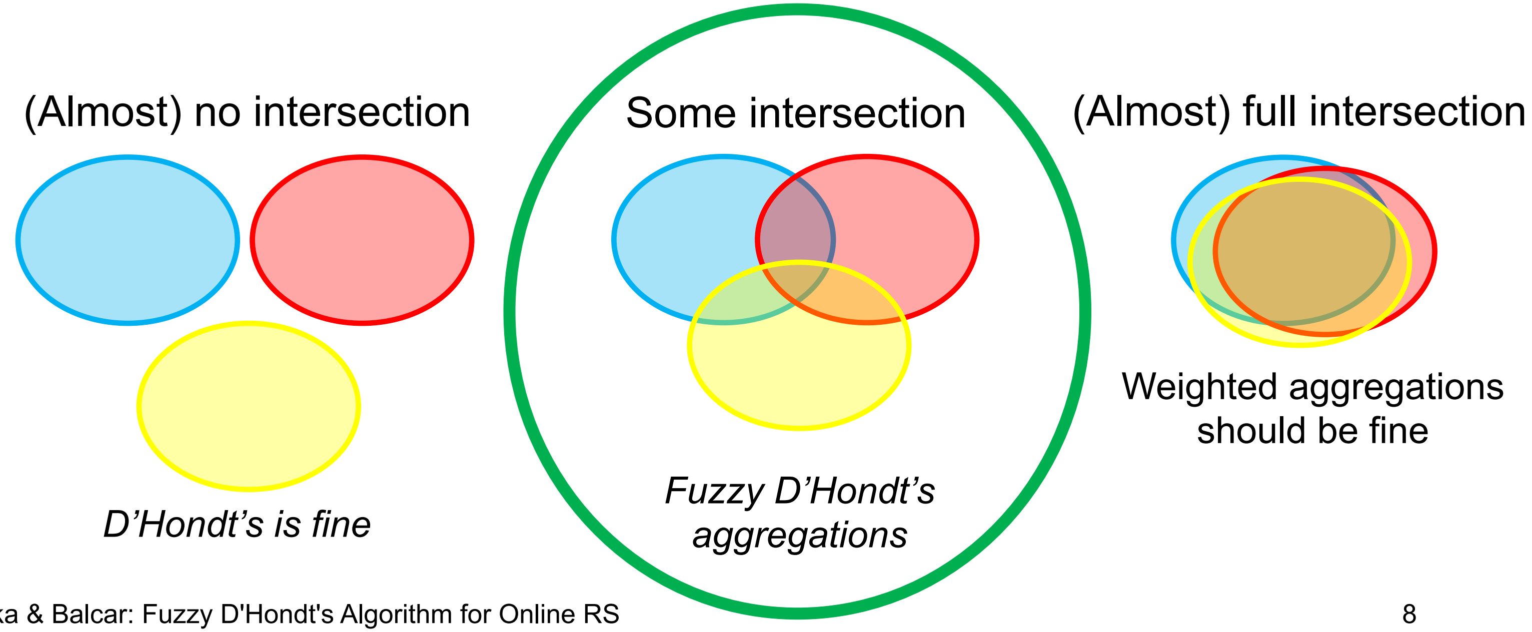
  - *But how large is the intersection?*

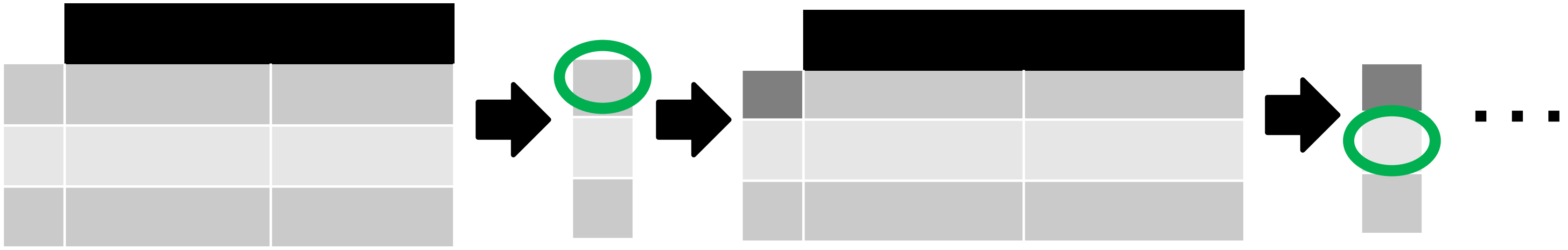


Fuzzy D'Hondt's RS Aggregations

- *Parties = RS strategies, Candidates = Items*
  - **Item can be recommended by multiple RS with varying relevance score**
    (unit vector normalization per RS)
  - Selecting best candidate w.r.t. current per-party votes and party-candidate relevance score

$$c_{best} = argmax_{\forall c_i \in C}\left(\sum_{p_i \in P} v_{curr,i} \times r_{i,j}\right)$$

  - Reduce per-party votes based on the party-candidate relevance $k_i \mathrel{+}= r_{i,best}$, $v_{curr,i} = \frac{v_{orig,i}}{k_i+1}$
  - Iterate until the desired volume of candidates is selected



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But who will assign the votes?

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This is beyond the hybridization problem... Anyway, we changed the technique recently

Also, where is the „on-line“ from the title?

Iterative Votes Assignments

- *Idea: More votes for methods recommending successful candidates and vice versa.*
- Optimizing criteria: maximize the difference of votes for good and bad candidates

$$\max\Big(\sum_{\forall c_j \in \mathcal{F}^+}\big(\sum_{\forall p_i \in \mathcal{P}} v_i * r_{i,j}\big) - \lambda_{neg}\sum_{\forall c_j \in \mathcal{F}^-}\big(\sum_{\forall p_i \in \mathcal{P}} v_i * r_{i,j}\big)\Big)$$

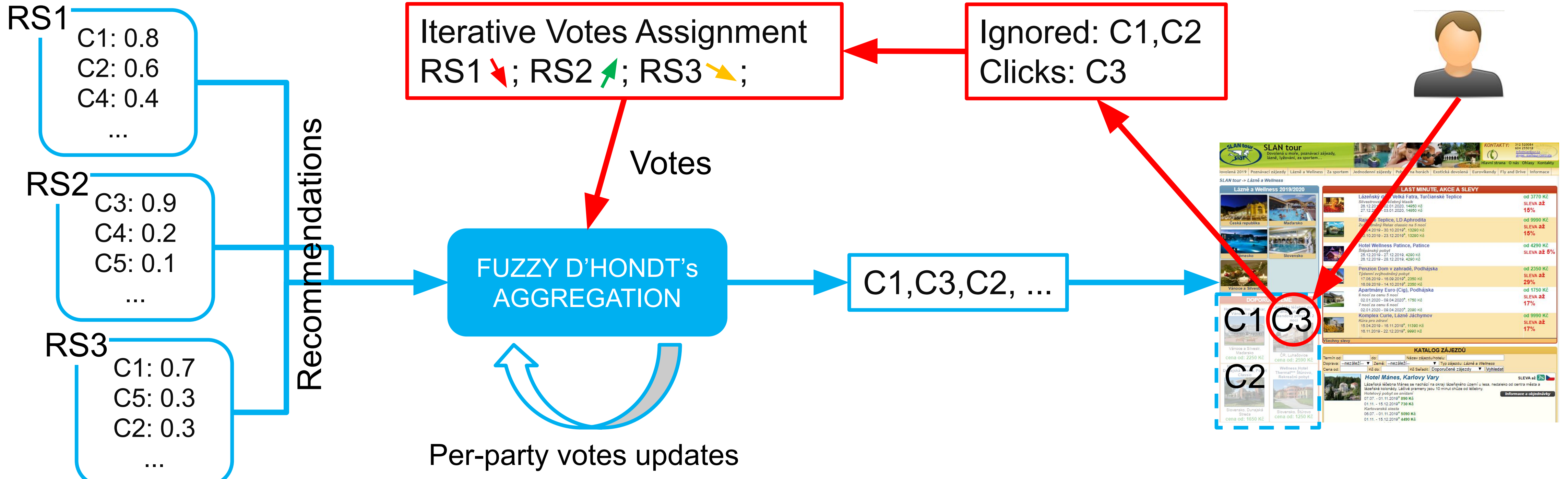
- Single SGD step upon registering each positive or negative feedback event
  - Positive: clicks on recommended items
  - Negative: ignoring items *(weak feedback, low λ_{neg})*
  - *Afterwards, normalize $\sum v_i = 1$*

$$v_i = v_i + \eta_{pos} * \big(r_{i,j} - \sum_{\forall k \neq i} r_{k,j}\big)$$

$$v_i = v_i - \eta_{neg} * \big(r_{i,j} - \sum_{\forall k \neq i} r_{k,j}\big)$$

  - *Adapting on performance changes over time*
  - *Can be pre-set based on previous performance*
  - *Can be fine-tuned for individual (long-term) users*

Overview of the Fuzzy D'Hondt's Aggregations



Evaluation Procedure

- Travel agency website, procedure based on our previous work[Peska 2018]
- Several RS: doc2vec (tours description), CB attributes similarity and CF word2vec
  - Recommendations for short sections of user's history
  - Selecting from previously best-performing algorithms: 4 base RS

- On-line A/B testing *(one RS strategy per user)*, July 2019
  - Two best-performing individual RS (Cosine CB, word2vec)
  - Fuzzy D'Hondt's Aggregations (4 base RS)
  - BEER(TS, SB): multiarmed bandits with Thompson sampling [Broden 2018] (4 base RS)

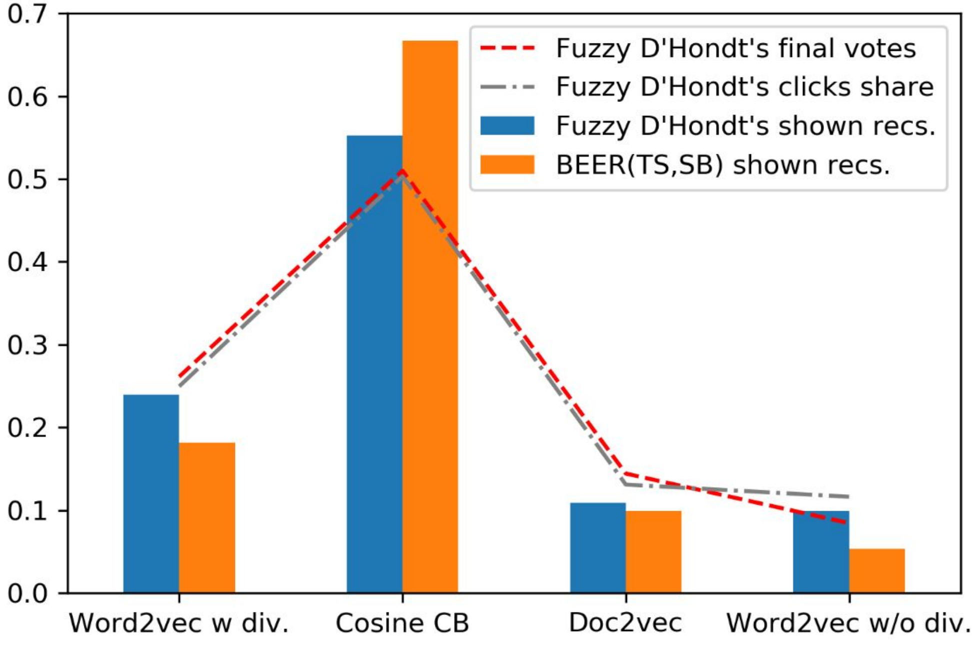
- Click through rate (CTR), visits after recommendation (VRR)
  - Aggregated per recommendation and per user

[Broden 2018] Bjorn Broden et al. Ensemble recommendations via thompson sampling: An experimental study within e-commerce. IUI 2018
[Peska 2018] Peska & Vojtas, Off-line vs. On-line Evaluation of Recommender Systems in Small E-commerce. REVEAL (RecSys) 2018

Results

- In total 2 299 users, 78 356 recommended objects, 7 663 #VRR, 576 #CTR
- Fuzzy D’Hondt’s achieved best scores in VRR and VRR per user
- The representation of individual base RS in results seems fair considering their final votes and click-through shares
- *Fuzzy D’Hondt’s recommendations are rather static -> lower CTR compared to Bandits?*

	CTR	VRR	CTR_U	VRR_U
Cosine CB	**.0086**	0.089	0.262	2.707
Word2vec	.0071	0.104	0.220	3.250
BEER(TS,SB)	.0077	0.078	**0.282**	2.861
Fuzzy D'Hondt's	.0063	**0.118**	0.239	**4.504**



Conclusions & Outlook

- Fuzzy extension of D’Hondt’s election algorithm with iterative votes assignment can be used to aggregate multiple RS strategies w.r.t. the principle of proportionality

  - Only the basic algorithm variant explored
    - *Better definition (learning?) of positive-negative feedback threshold*
    - *More refined feedback definition (e.g., actions after click, negative only if visible) - depends on domain*
    - *Stochastic candidates selection*
    - *Penalize candidates relevance through time*

  - More extensive evaluation needed
    - *Additional domains & baselines*
    - *Analyze domain parameters (RS diversity etc.)*

Thank you!

Questions, comments?