

Benefits of Diverse News Recommendations for Democracy

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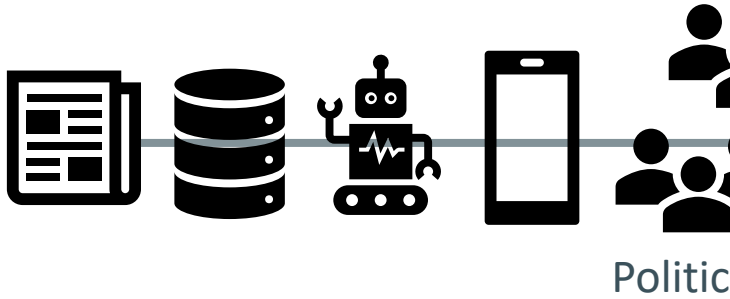
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News recommenders could

- a) create selfreinforcing biases that **damage** public debates (Milano et al., 2020)
- b) powerful tools to shape public opinion and serve as a foundation for **public cohesion** (Bernstein et al., 2021)

Background

Experimental design



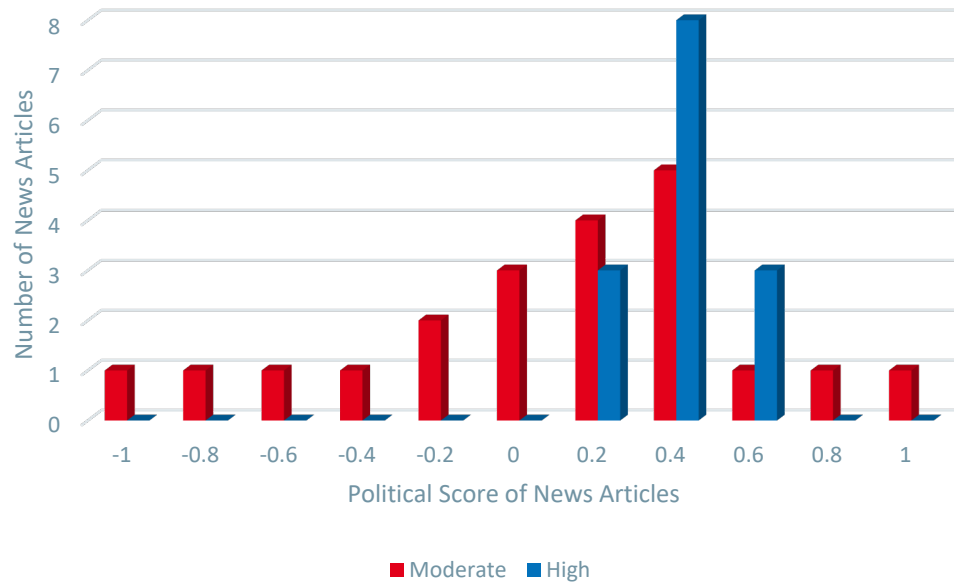
Kanadier haben die Schönste: Neues 200er-Nötli war chancenlos

Jahr für Jahr werden die schönsten Banknoten der Welt prämiert. Für einmal musste sich die Schweiz geschlagen geben.

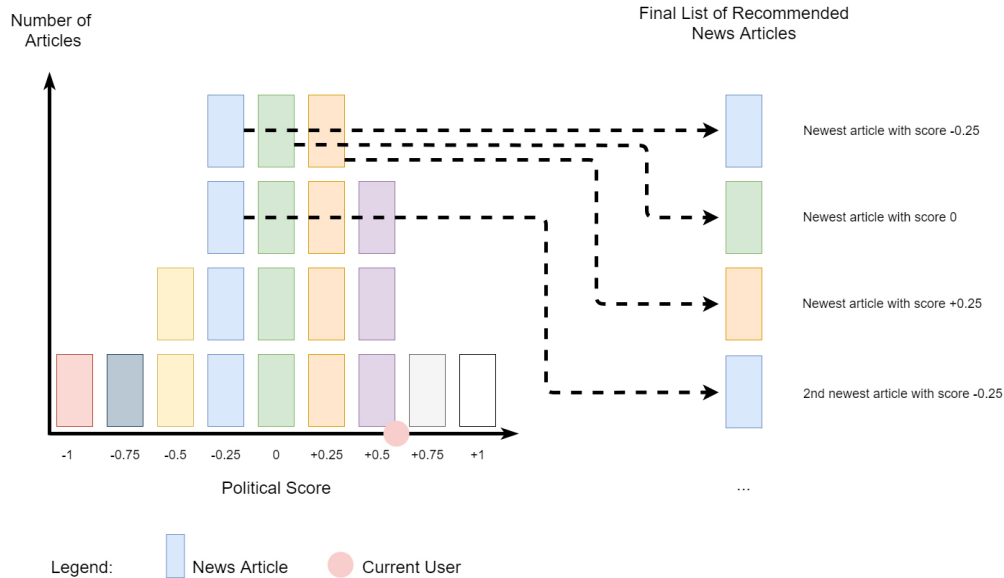
Heute, 18:30 Uhr



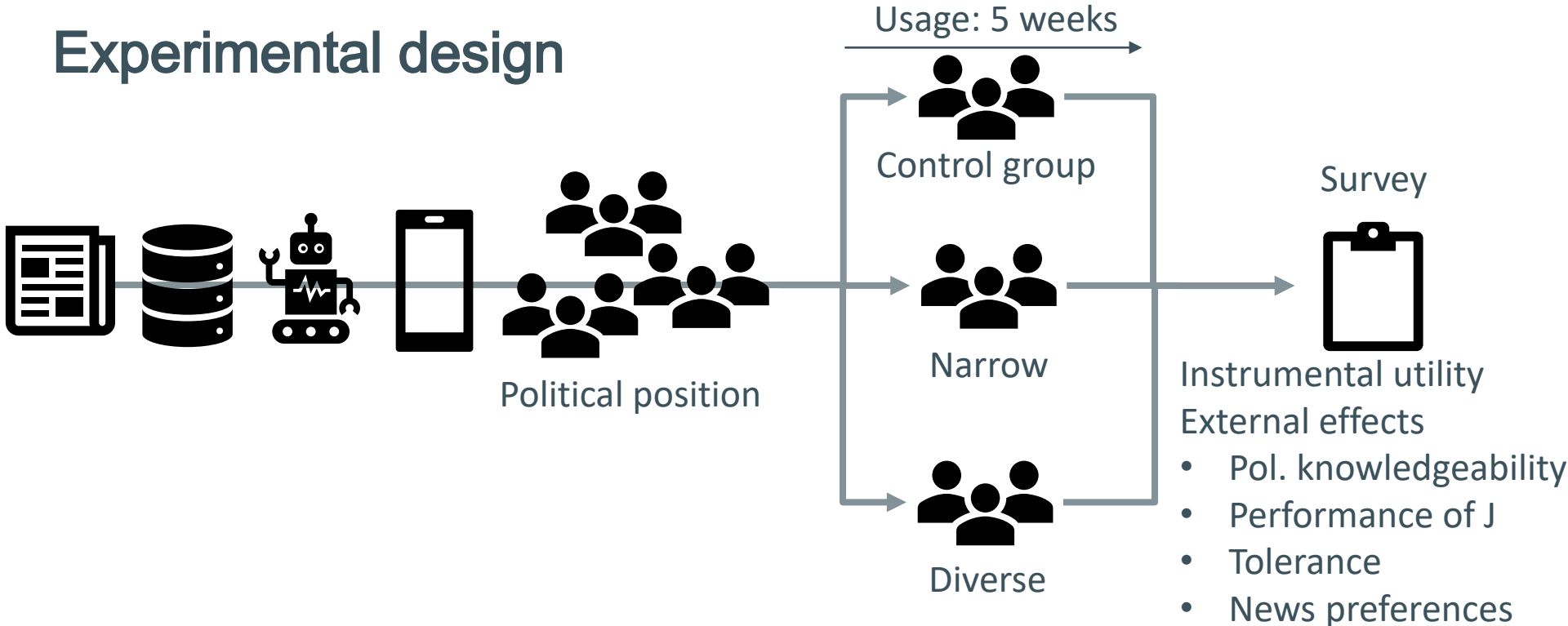
Narrow vs. diverse recommendations for a 0.4 user



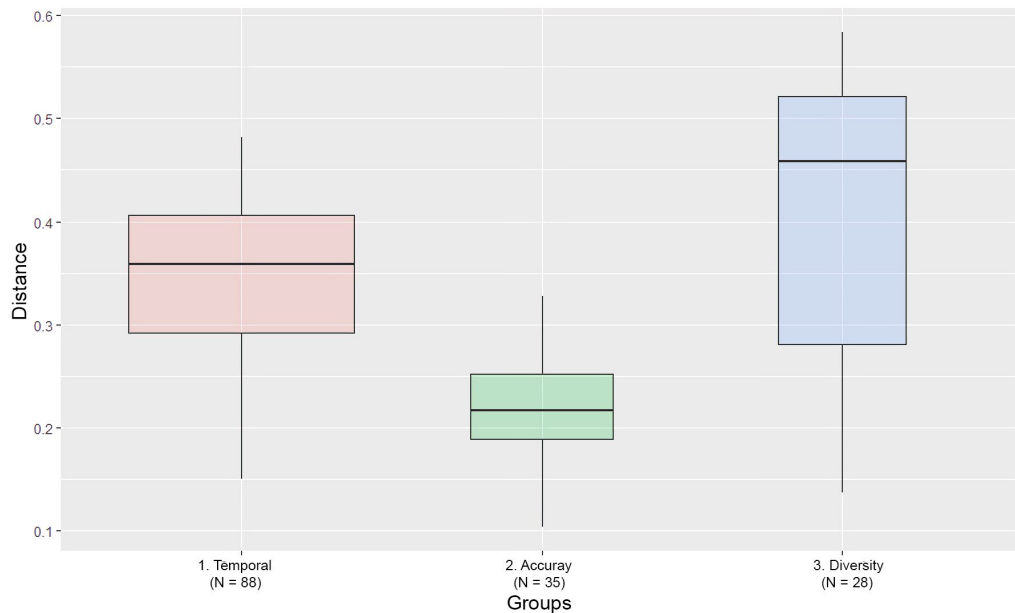
From article distribution to recommendation list



Experimental design



Article use and article distances



Surveyresults (1/2)

	Instrumental utility			Political interest			Political participation		
	β	ρ	η_p^2	β	ρ	η_p^2	β	ρ	η_p^2
Constant	3.668	0.000	0.468	1.227	0.004	0.057	2.242	0.000	0.233
Diversity Group	0.284	0.495	0.003	0.573	0.279	0.008	-0.136	0.754	0.001
Narrow Group	0.391	0.254	0.009	0.662	0.128	0.017	-0.144	0.686	0.001
Political position	0.037	0.900	0.000	0.270	0.476	0.004	-0.034	0.912	0.000
App usage (hrs)	0.020	0.009	0.048	-0.004	0.670	0.001	0.013	0.113	0.018
Ext. news usage	0.014	0.047	0.028	0.020	0.024	0.036	0.023	0.002	0.069
Gender (f = 1; m = 2)	-0.035	0.783	0.001	0.702	0.000	0.123	0.370	0.005	0.055
Age (y)	-0.005	0.241	0.010	-0.001	0.898	0.000	0.000	0.976	0.000
Education	-0.047	0.068	0.024	0.020	0.530	0.003	0.077	0.005	0.057
Diversity x Pol. pos.	-0.424	0.537	0.003	-0.855	0.329	0.007	-0.016	0.982	0.000
Narrow x Pol. pos.	-0.845	0.123	0.017	-0.558	0.421	0.005	0.185	0.745	0.001
<i>F</i> (<i>p</i>)	1.862 (.055)			4.467 (.000)			5.483 (.000)		
Adj. <i>R</i> ²	.055			.189			.231		
df	139, 10			139, 10			139, 10		

Surveyresults (2/2)

	Social performance of journalism			Tolerance for opposing views			News preferences for opposing views			News preferences for majority views		
	β	ρ	η_p^2	β	ρ	η_p^2	β	ρ	η_p^2	β	ρ	η_p^2
Cons.	1.465	0.000	0.087	2.869	0.000	0.401	2.937	0.002	0.068	3.770	0.000	0.090
Div.	1.098	0.032	0.033	1.443	0.000	0.097	0.903	0.054	0.026	0.748	0.159	0.014
Nar.	0.883	0.033	0.032	0.577	0.061	0.025	0.487	0.204	0.012	0.955	0.025	0.036
Pol. pos.	0.731	0.046	0.029	0.850	0.002	0.068	0.373	0.265	0.009	0.554	0.134	0.016
App use	0.012	0.195	0.012	0.013	0.062	0.025	0.022	0.009	0.049	0.017	0.060	0.025
Ext. news	0.009	0.263	0.009	0.018	0.005	0.055	0.026	0.000	0.088	0.013	0.095	0.020
Gender	0.140	0.361	0.006	-0.059	0.603	0.002	-0.065	0.647	0.002	-0.144	0.359	0.006
Age (y)	-0.003	0.574	0.002	-0.011	0.005	0.056	-0.553	0.506	0.003	-0.708	0.441	0.004
Edu.	0.100	0.002	0.070	0.068	0.004	0.059	0.008	0.768	0.001	-0.043	0.173	0.013
Div.xPos.	-1.628	0.053	0.027	-2.567	0.000	0.111	-1.200	0.122	0.017	-0.598	0.492	0.003
Nar.xPos.	-1.052	0.111	0.018	-0.813	0.098	0.020	-0.687	0.263	0.009	-1.289	0.058	0.026
$F(p)$	2.978 (.002)			4.971 (.000)			2.755 (.004)			1.635 (.103)		
Adj. R^2	.119			.210			.105			.041		
df	137, 10			139, 10			139, 10			139, 10		

1. Audiences find diverse news just as useful
 2. Diverse news may induce tolerance, especially for conservative users
 3. Diverse news can nudge users to prefer diverse news diet
- Diverse recommendations may have a de-polarizing capacity

Conclusion

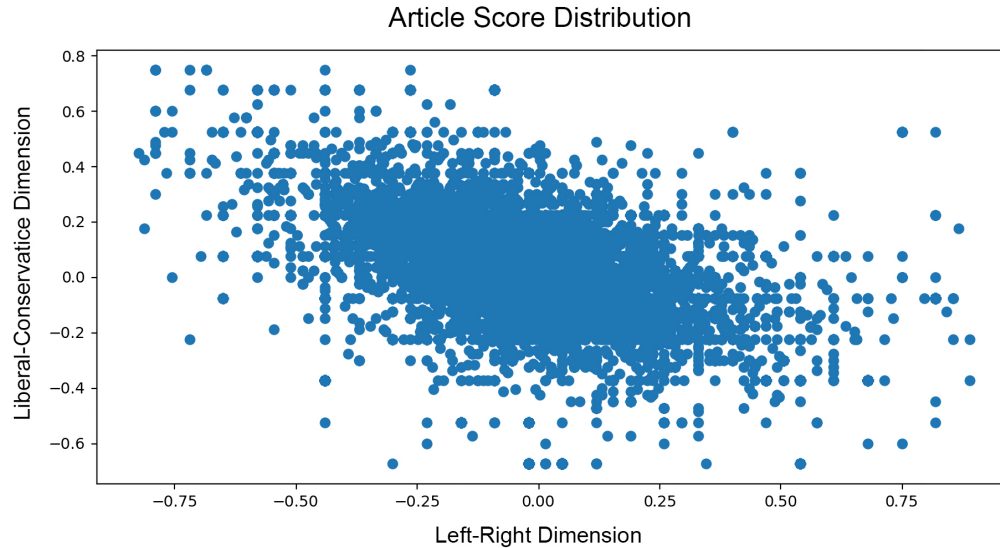
From article distribution to recommendation list

Algorithm 1: Translation Algorithm

```
Input :  $score_u, art\_distribution$  //  $art\_distribution$  defined as list of tuples  $score_a, n_a$ 
Output:  $desired\_distribution$ 

1  $max = maxScore(art\_distribution)$  // find largest value of  $n_a$  among all tuples
2  $desired\_distribution = []$  // initialize recommendation list
3 while  $maxScore(art\_distribution) > 1$  do
4    $tuples_{filter} = filterTuples(art\_distribution, max)$  // get tuples of  $art\_distribution$  where  $n_a = max$ 
5    $tuple_{max} = maxDistance(tuples_{filter}, score_u)$  // get tuple where  $|score_a - userScore|$  is maximal
6    $appendScore(tuple_{max}, desired\_distribution)$  // add  $score_a$  of  $tuple_{max}$  to  $desired\_distribution$ 
7    $reduceCount(tuple_{max})$  // decrement  $n_a$  of  $tuple_{max}$  by 1
8   if  $maxScore(art\_distribution) \neq max$  then
9      $max = max - 1$ 
10 return  $desired\_distribution$ 
```

Article scoredistribution



- 1.
- 2.
- 3.

Outlook



Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG



Universität
Zürich^{UZH}

Thank you!