## Learning from Human-Generated Lists

Kwang-Sung Jun (deltakam@cs.wisc.edu)

Department of Computer Sciences, University of Wisconsin-Madison

Xiaojin (Jerry) Zhu (jerryzhu@cs.wisc.edu)

Department of Computer Sciences, University of Wisconsin-Madison

Burr Settles (burrsettles@gmail.com) Duolingo

Timothy Rogers (ttrogers@wisc.edu) Department of Psychology, University of Wisconsin-Madison

ICML'13

Example 1:

# "List examples of animals without repetition for 60 seconds."



Order	Item
1	dog
2	cat
3	tiger
4	cow
•••	•••
7	lion
8	tiger
9	bear
•••	•••
11	armadillo

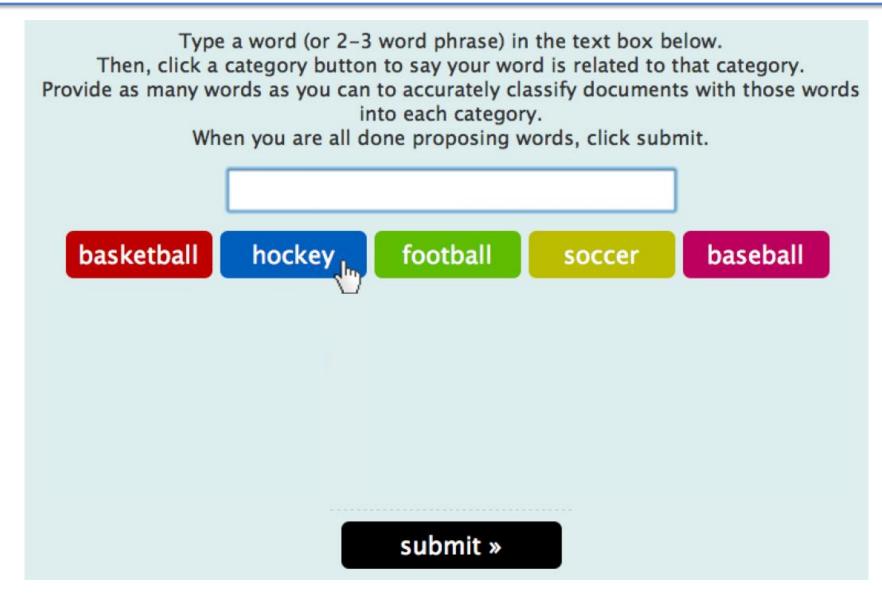
Example 1: Verbal Fluency

# "List examples of animals without repetition for 60 seconds."

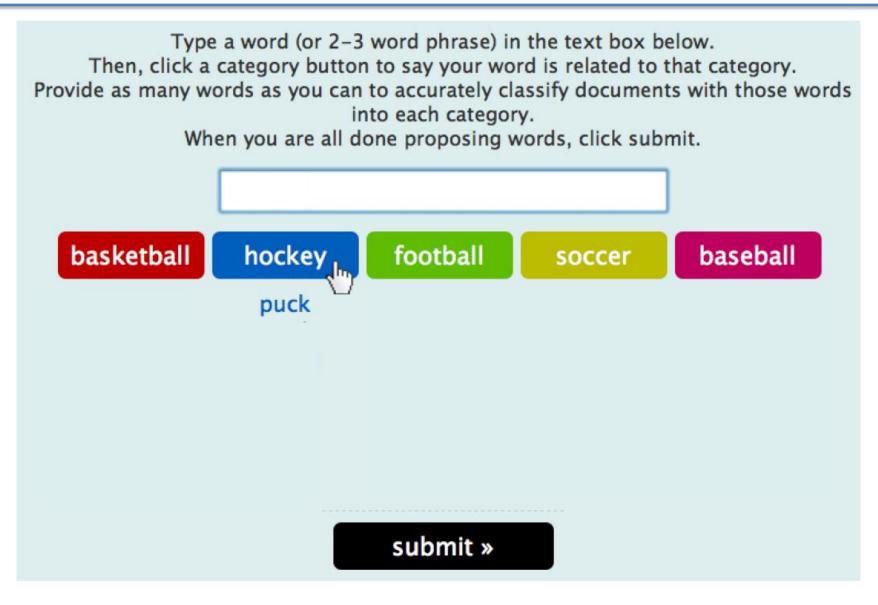


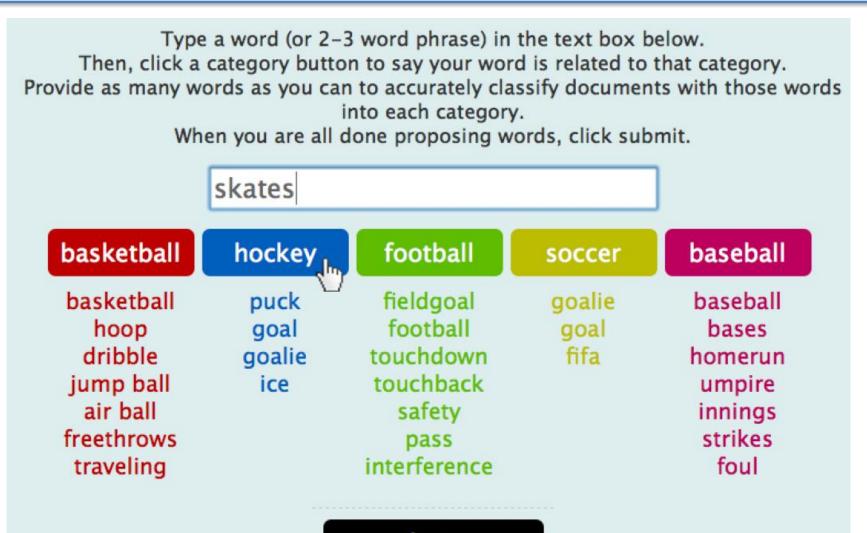
Order	Item
1	dog
2	cat
3	tiger
4	cow
•••	•••
7	lion
8	tiger
9	bear
•••	•••
11	armadillo

- Simple rules: e.g. skates  $\Rightarrow$  hockey
  - IF a document contains the word skates, THEN label the document as hockey.









submit »

Order	Item
1	baseball bat $\Rightarrow$ Baseball
•••	•••
7	quarterback $\Rightarrow$ Football
8	football field $\Rightarrow$ Football
9	soccer ball $\Rightarrow$ Soccer
•••	•••
23	basketball court $\Rightarrow$ Basketball
24	football field $\Rightarrow$ Football
25	soccer field $\Rightarrow$ Soccer
•••	•••

#### Characteristics of Human-Generated Lists

- Order matters
- Repeats happen

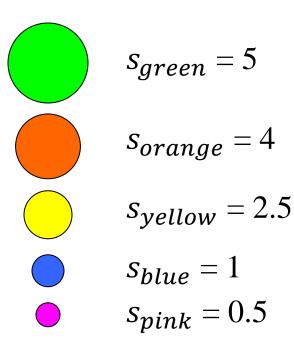
Order	Item	Order	Item
1	dog	1	baseball bat $\Rightarrow$ Baseball
2	cat	•••	•••

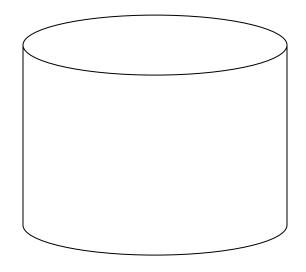
#### Sampling WIth Reduced repLacement (SWIRL)

7	lion
8	tiger
9	bear
•••	•••
11	armadillo

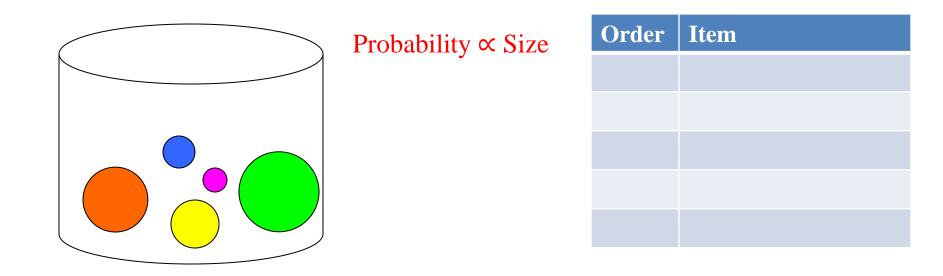
•••	
23	basketball court $\Rightarrow$ Basketball
24	football field $\Rightarrow$ Football
25	soccer field $\Rightarrow$ Soccer
•••	•••

•  $s_i$ : size of the ball *i* 

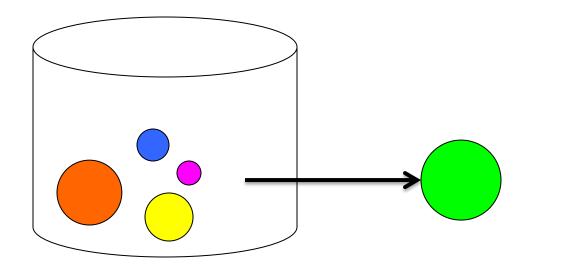




- $s_i$ : size of the ball *i*
- iteration 1:

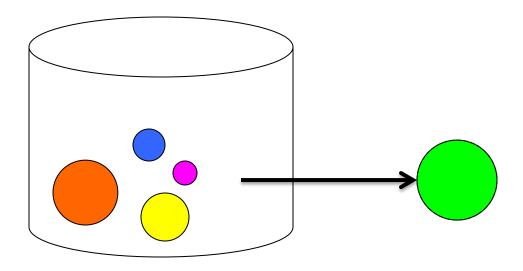


- $s_i$ : size of the ball *i*
- iteration 1:



Item

- $s_i$ : size of the ball *i*
- iteration 1:



Order	Item
1	Green

• α: discount factor

- $s_i$ : size of the ball *i*
- iteration 1:

 Order
 Item

 1
 Green

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

 0
 0

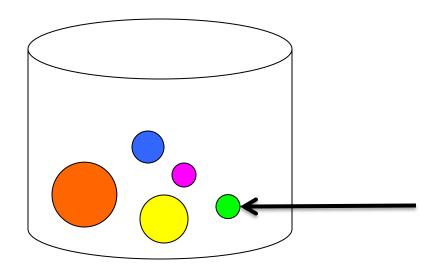
 0
 0

 0
 0

 0
 0

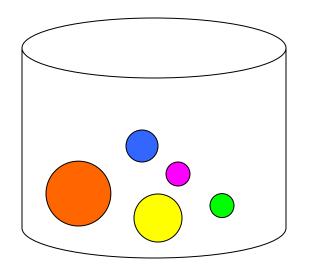
 $s_{green} \leftarrow \alpha s_{green}$ 

- $s_i$ : size of the ball i  $\alpha$ : discount factor
- iteration 1:



Order	Item
1	Green

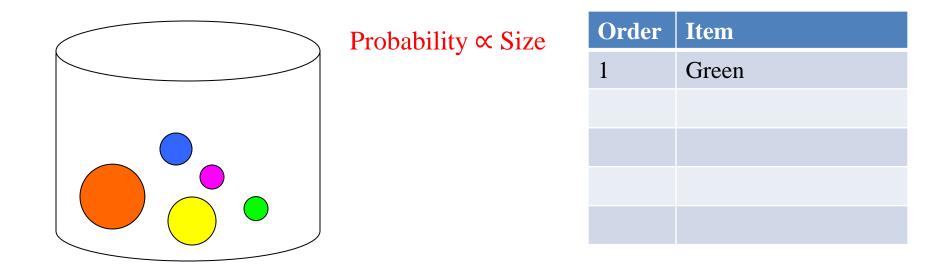
- *s<sub>i</sub>*: size of the ball *i*
- iteration 1:



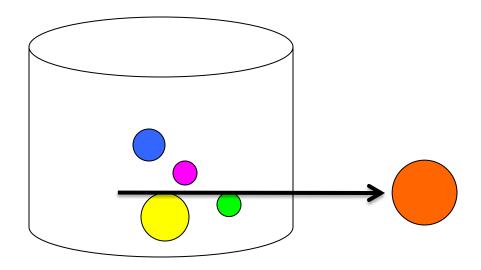
Order	Item
1	Green

• α: discount factor

- $s_i$ : size of the ball i  $\alpha$ : discount factor
- iteration 2:



- $s_i$ : size of the ball i  $\alpha$ : discount factor
- iteration 2:



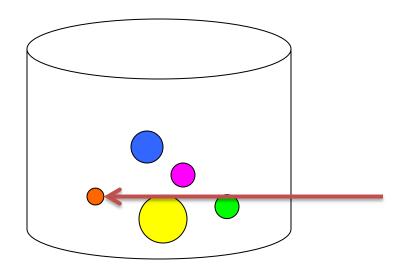
Order	Item
1	Green
2	Orange

- $s_i$ : size of the ball i  $\alpha$ : discount factor
- iteration 2:

	Order	Item
	1	Green
	2	Orange
>.		

 $s_{orange} \leftarrow \alpha s_{orange}$ 

- $s_i$ : size of the ball *i*
- iteration 2:



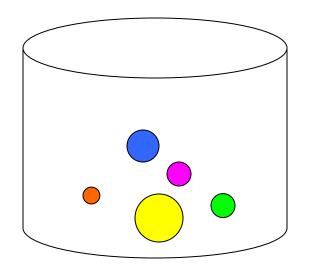
OrderItem1Green

Orange

2

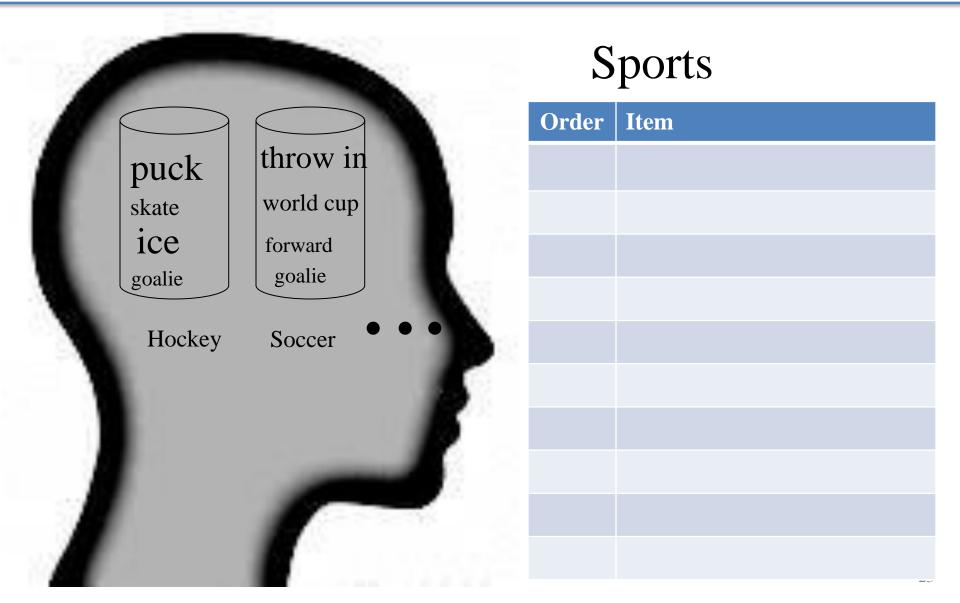
• α: discount factor

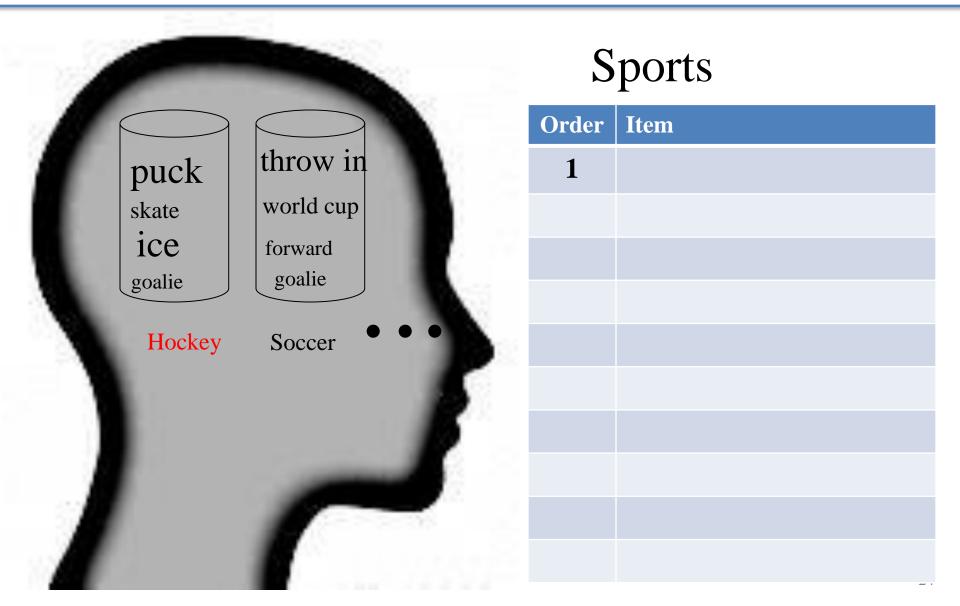
- $s_i$ : size of the ball *i*
- iteration 2:

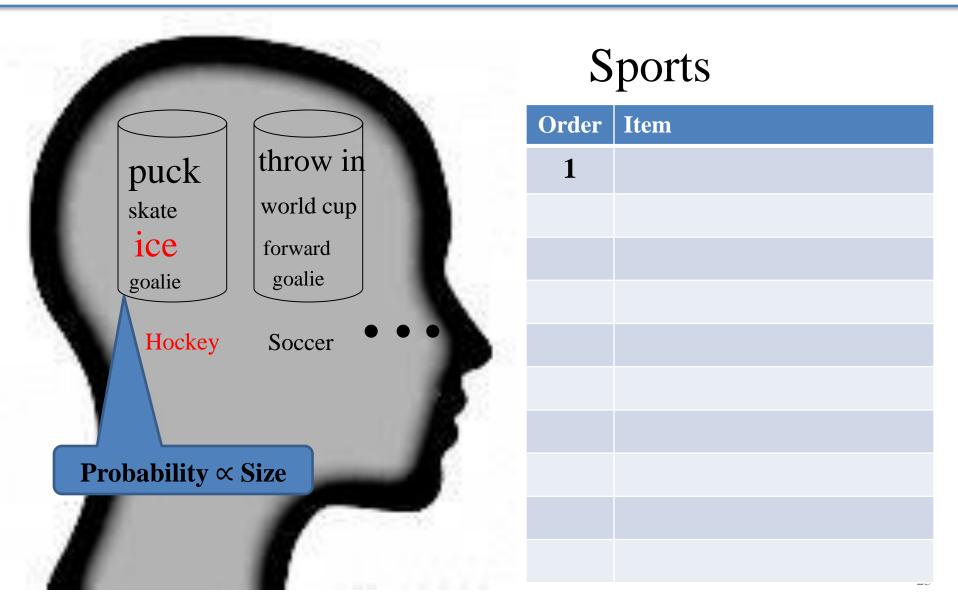


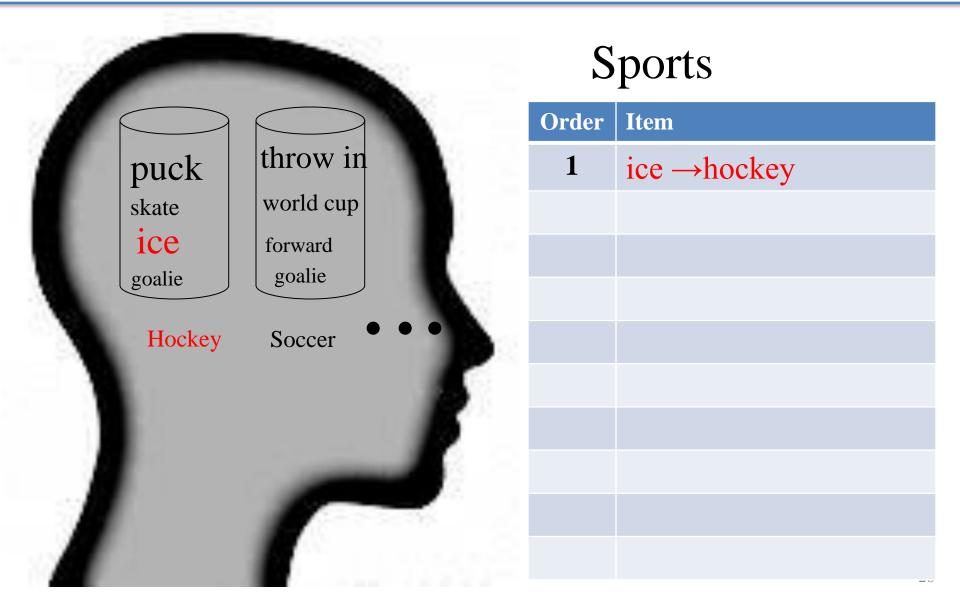
α: discount factor

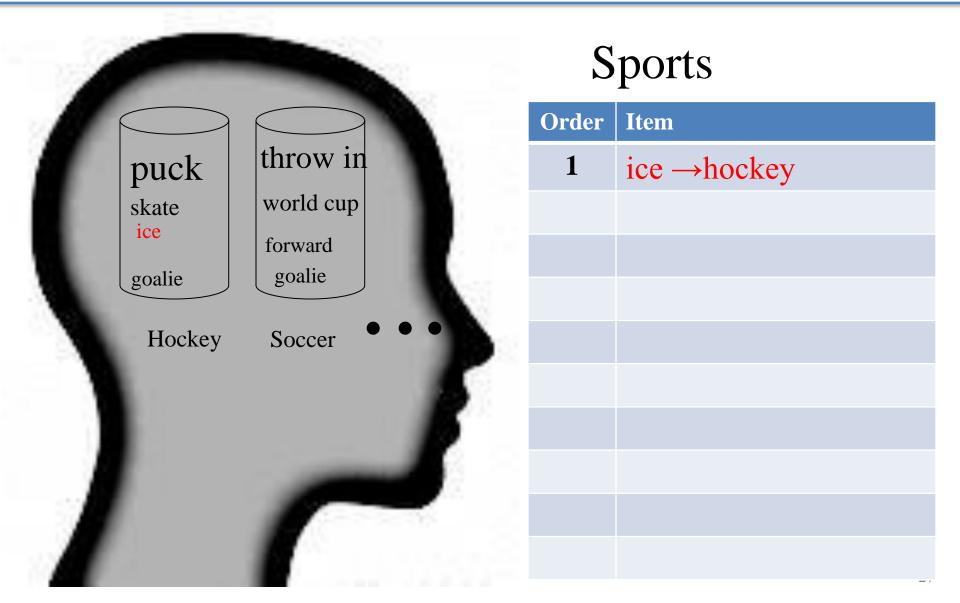
Order	Item
1	Green
2	Orange

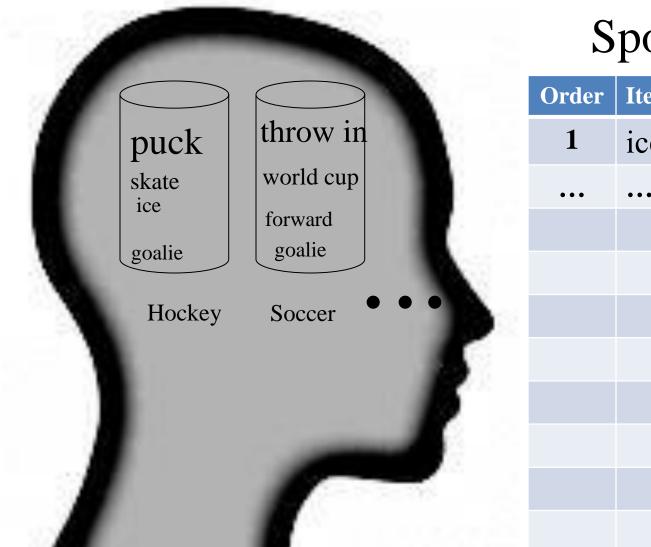












# Sports

Order	Item
1	ice →hockey
•••	•••

- Input:  $\mathbf{s} = \{s_i \mid i \in V\}, \lambda, \alpha$
- $n \sim \text{Poisson}(\lambda)$
- for t = 1, ..., n do

$$- z_t \sim \text{Multinomial}\left(\frac{s_i}{\sum_{j \in V} s_j} \mid i \in V\right)$$

$$-s_{z_t} \leftarrow \alpha s_{z_t}$$

- end for
- Output:  $(z_1, ..., z_n)$

## Maximum Likelihood Estimate

- Observed Lists:  $\mathbf{z}^{(1)} = \left(z_1^{(1)}, \dots, z_{n^{(1)}}^{(1)}\right), \dots, \mathbf{z}^{(N)} = \left(z_1^{(N)}, \dots, z_{n^{(N)}}^{(N)}\right)$
- $n^{(j)}$ : list length of  $\mathbf{z}^{(j)}$

$$\ell = \sum_{j=1}^{N} n^{(j)} \log \lambda - \lambda + \sum_{t=1}^{n^{(j)}} \log P\left(z_t^{(j)} \mid z_{1:t-1}^{(j)}, \mathbf{s}, \alpha\right)$$

- MLE =  $(\hat{\lambda}, \hat{\alpha}, \hat{s})$
- Optimization
  - -s is scale invariant: constrain most frequent item's size to 1
  - L-BFGS
  - Concave log likelihood

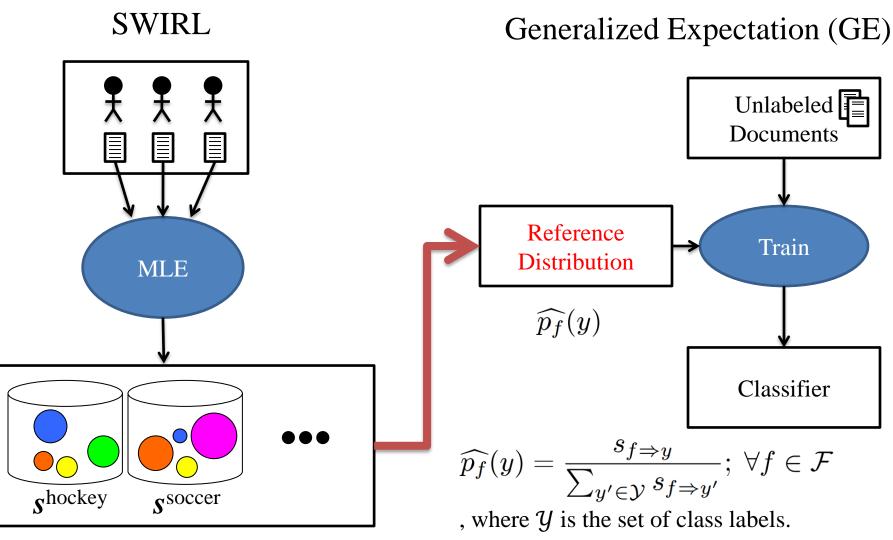
## Application 1: Learning by Feature Volunteering

- Train a text classifier by volunteering feature-label pairs
  - Generalized Expectation (GE) [Druck08]
  - Informative Dirichlet Prior (IDP) [Settles11]



Order	Item
1	baseball bat $\Rightarrow$ Baseball
••••	
7	quarterback $\Rightarrow$ Football
8	football field $\Rightarrow$ Football
9	soccer ball $\Rightarrow$ Soccer
•••	•••
23	basketball court $\Rightarrow$ Basketball
24	football field $\Rightarrow$ Football
25	soccer field $\Rightarrow$ Soccer
•••	•••

## Application 1: Learning by Feature Volunteering



## Application 1: Learning by Feature Volunteering

Domoin	Class Labels	Lists		Documents		<b>Reference Distributions</b>			
Domain Class Labels	Class Labels	N	$ \mathcal{F} $	$ \mathcal{U} $	$ \mathcal{F}^+ $	SWIRL	Equal	Schapire	FV
sports	baseball, basketball, football, hockey, soccer	52	594	1123	2948	0.865	0.847	0.795	0.875
movies	negative, positive	27	382	2000	2514	0.733	0.733	0.725	0.681
webkb	course, faculty, project, student	56	961	4199	2521	0.463	0.444	0.429	0.426

*N*: the # of subjects,  $\mathcal{F}$ : the set of features (phrases) volunteered in *N* lists,  $\mathcal{U}$ : the set of unlabeled documents, and  $\mathcal{F}^+$ : union of  $\mathcal{F}$  and unigrams in  $\mathcal{U}$ .

**SWIRL**:  $\widehat{p_f}(y) = \frac{s_{f \Rightarrow y}}{\sum_{y' \in \mathcal{Y}} s_{f \Rightarrow y'}}; \forall f \in \mathcal{F}$ , where  $\mathcal{Y}$  is the set of class labels.

Equal: 
$$\widehat{p_f}(y) = \frac{\mathbbm{1}\{s_{f\Rightarrow y} > 0\}}{\sum_{y'\in\mathcal{Y}} \mathbbm{1}\{s_{f\Rightarrow y'} > 0\}}; \ \forall f \in \mathcal{F}$$

Schapire: Smoothed Equal used in [Druck08]

**FV**: Feature Voting. Non-GE baseline.

Application 2: Verbal Fluency

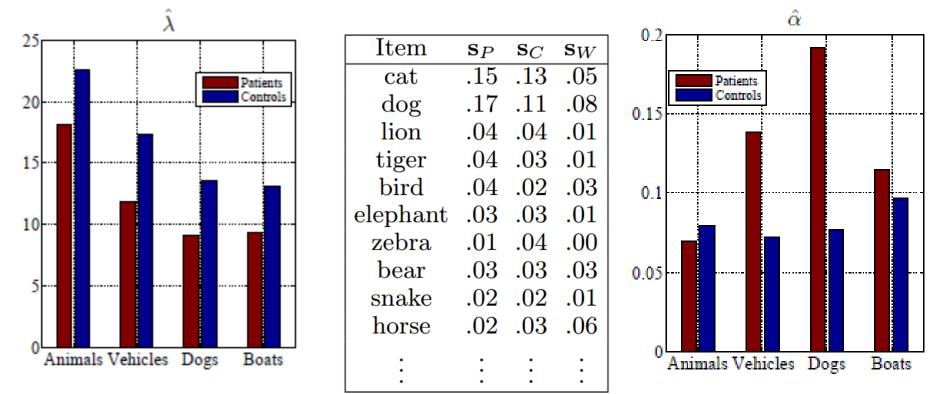
# "List examples of animals without repetition for 60 seconds."

- 27 patients / 24 healthy people
- Categories:
  - animals
  - vehicles
  - dogs
  - boats

Order	Item
1	dog
2	cat
3	tiger
4	cow
•••	•••
7	lion
8	tiger
9	bear
•••	•••
11	armadillo

**Application 2: Verbal Fluency** 

 $(\hat{\lambda}, \hat{\alpha}, \hat{s})_{patients}$  vs.  $(\hat{\lambda}, \hat{\alpha}, \hat{s})_{healthy}$ 



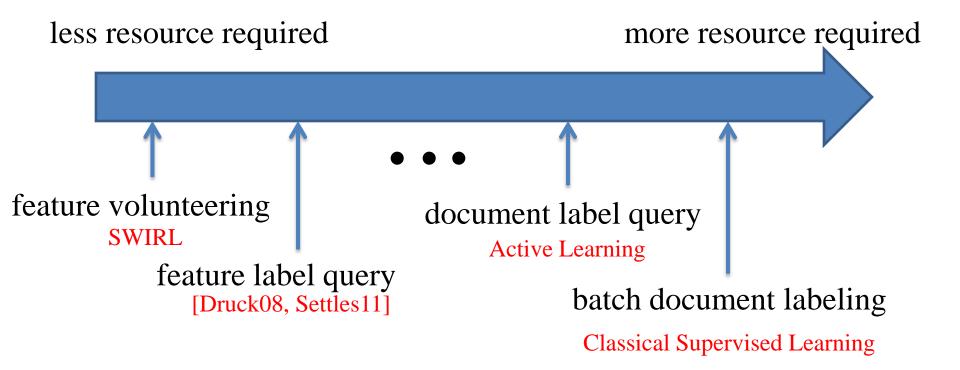
## Application 2: Verbal Fluency

• Patient vs. healthy classification

Animals	Vehicles	Dogs	Boats	Majority Vote
0.647	0.706	0.784	0.627	0.529

#### Future Work

• Supervision pipeline



#### Future Work

- More applications
  - e.g. Hashtags



Tags
salisbury collection salisbury collection
slide old photo 35mm camera found
found slide found slides 1959 slides
vintage car cars car ferry ferry
tellsprung mountain mountains june 1959
june europe 1959 their car

#### Future Work

• Hierarchical SWIRL: individual level parameters as well as group level parameters.

• Structured SWIRL: "runs" of semantically-related items

Order	Item
1	dog
2	cat
3	tiger
4	cow
•••	•••
7	lion
8	tiger
9	bear
•••	•••
11	armadillo

#### Human-generated lists are interesting, and SWIRL can make them useful!

Code & data are available at: <u>http://pages.cs.wisc.edu/~deltakam</u> (or google "Kwang-Sung Jun").

#### Acknowledgements

The authors were supported in part by National Science Foundation grants IIS-0953219, IIS-0916038, IIS-1216758, IIS-0968487, DARPA, and Google. The patient data was collected under National Institute of Health grant R03 NS061164 with TR as the PI. We thank Bryan Gibson for help collecting the feature volunteering data and students and faculties in UW-Madison for providing feedbacks.