## Quantifier Distribution and Semantic Complexity

Camilo Thorne ${ }^{1}$ Jakub Szymanik ${ }^{2}$<br>${ }^{1}$ KRDB Research Centre for Knowledge and Data<br>cthorne@inf.unibz.it<br>http://www.inf.unibz.it/~cathorne<br>${ }^{2}$ Institute for Logic, Language and Computation<br>jakub.szymanik@gmail.com<br>http://www.jakubszymanik.com/

TbiLLC2013, Sep 26, Tbilisi


## Motivation



- Words and structures in English occur following some general laws
- A distribution describes how often they occur/probable they are
- E. Zipf showed that in many cases such distributions correspond to power laws


## Hypothesis

Quantifiers are power-law distributed w.r.t. semantic complexity


## Motivation (ctd.) I

the total area of Europe is greater than 5,000,000 km2
the highest mountain in Peru is the Huascaran the average height of men in France is 180 cm less than one fifth of Brazilians like cricket the product mass of atoms is finite more than one third of MPs sit next to each other most people procrastinate

爻

## Motivation (ctd.) II

the total area of Europe is greater than $5,000,000 \mathrm{~km} 2$
the highest mountain in Peru is the Huascaran the average height of men in France is 180 cm
less than one fifth of Brazilians like cricket
the product mass of atoms is finite
more than one third of MPs sit next to each other
most people procrastinate


## Motivation (ctd.) III

the total area of Europe is greater than $5,000,000 \mathrm{~km} 2$
the highest mountain in Peru is the Huascaran the average height of men in France is 180 cm
less than one fifth of Brazilians like cricket the product mass of atoms is finite more than one third of MPs sit next to each other most people procrastinate


## Motivation (ctd.) IV

the total area of Europe is greater than $5,000,000 \mathrm{~km} 2$
the highest mountain in Peru is the Huascaran
the average height of men in France is 180 cm
less than one fifth of Brazilians like cricket
the product mass of atoms is finite
more than one third of MPs sit next to each other
most people procrastinate


## Outline

(1) Background
(2) Generalized Quantifiers

- Reminder
- Expressive Power
(3) Semantic Complexity
- Tractable Quantifiers
- Intractable Quantifiers
(4) Quantifier Distribution
- Power Laws
- Corpora
- Results
(5) Conclusions
(6) References
(7) Appendix


## English Generalized Quantifiers [BC80]

## Definition (Generalized Quantifier)

Given $\mathcal{I}$, a generalized quantifier $Q$ of type $\left(k_{1}, \ldots, k_{n}\right)$ is a relation of tuples $\left(R_{1}, \ldots, R_{n}\right)$ s.t., for $1 \leq i \leq k, R_{i} \subseteq \Delta^{k_{i}}$.

- English generalized quantifiers are realized by Dets and NPs
- They state relations that hold over properties in a model

$$
\begin{aligned}
\llbracket \mathrm{no} \rrbracket & =\{(A, B) \subseteq \Delta \times \Delta \mid A \cap B=\emptyset\} \\
\llbracket \text { every } \rrbracket & =\{(A, B) \subseteq \Delta \times \Delta \mid A \subseteq B\} \\
\llbracket \text { at least } k \rrbracket & =\{(A, B) \subseteq \Delta \times \Delta \mid \#(A \cap B) \geq k\} \\
\llbracket \text { some } \rrbracket & =\{(A, B) \subseteq \Delta \times \Delta \mid A \cap B \neq \emptyset\} \\
& \text { FOL quantifiers of type }(1,1)
\end{aligned}
$$

## Proportional and Aggregate Quantifiers

$$
\begin{aligned}
\llbracket \text { the number of } \rrbracket & =\{(A, B) \subseteq \Delta \times \Delta \mid \operatorname{count}(A) \in B\} \\
\llbracket \text { the average } \beta \text { of } \rrbracket & =\{(A, B) \subseteq \Delta \times \Delta \mid \operatorname{avg}(\beta(A)) \in B\} \\
\llbracket \text { the total } \beta \text { of } \rrbracket & =\{(A, B) \subseteq \Delta \times \Delta \mid \operatorname{sum}(\beta(A)) \in B\} \\
\llbracket \text { the } \beta \text {-est } \rrbracket & =\{(A, B) \subseteq \Delta \times \Delta \mid \operatorname{argmax}(\beta(A)) \in B\} \\
\llbracket \text { the product } \beta \text { of } \rrbracket & =\{(A, B) \subseteq \Delta \times \Delta \mid \operatorname{prod}(\beta(A)) \in B\}
\end{aligned}
$$

Aggregate quantifiers [Tho10] of type $(1,1)$

$$
\begin{aligned}
\llbracket \mathrm{most} \rrbracket & =\{(A, B) \subseteq \Delta \times \Delta \mid \#(A \cap B) \geq \#(A \backslash B)\} \\
\text { 【more than } n / k \text { of } & =\{(A, B) \subseteq \Delta \times \Delta \mid \#(A \cap B) \geq n / k \cdot \#(A)\}
\end{aligned}
$$

Proportional quantifiers of type $(1,1)$

## L-Expressibility

## Definition (L-Expressibility)

A quantifier $Q$ of type $\left(k_{1}, \ldots, k_{n}\right)$ is expressible in logic L iff there exists a formula $\bar{Q}\left(R_{1}, \ldots, R_{n}\right)$, with $R_{i}$ a relation symbol of arity $k_{i}$, for $1 \leq i \leq k$, such that, for all models $\mathcal{I}$,

$$
Q=\left\{\left(R_{1}^{\mathcal{I}}, \ldots, R_{n}^{\mathcal{I}}\right) \subseteq \Delta^{k_{1}} \times \cdots \times \Delta^{k_{n}} \mid \mathcal{I} \models \bar{Q}\left(R_{1}, \ldots, R_{n}\right)\right\}
$$

$$
\begin{aligned}
\llbracket \mathrm{no} \rrbracket & =\left\{\left(A^{\mathcal{I}}, B^{\mathcal{I}}\right) \subseteq \Delta \times \Delta|\mathcal{I}| \forall x(A(x) \Rightarrow \neg B(x))\right\} \\
\llbracket \text { some】 } & =\left\{\left(A^{\mathcal{I}}, B^{\mathcal{I}}\right) \subseteq \Delta \times \Delta|\mathcal{I}|=\exists x(A(x) \wedge B(x))\right\}
\end{aligned}
$$

Q: Are proportional and aggregate quantifiers more expressive or complex than FOL quantifiers?


## Expressiveness: $\operatorname{argmin}(\cdot), \operatorname{argmax}(\cdot)$

## Theorem

If we consider $\Delta$ ordered by $\leq$ then the functions $\operatorname{argmin}(\cdot)$ and $\operatorname{argmax}(\cdot)$ are FOL-expressible
$\triangleright$ Indeed, for all $\mathcal{I}$,

$$
\begin{gathered}
\mathcal{I} \models c \approx \underset{\text { iff }}{\operatorname{argmax}}(P) \\
\mathcal{I} \models \exists!x \forall y(P(x) \wedge P(y) \wedge x \geq y \wedge x \approx c)
\end{gathered}
$$

## Theorem

If we order the domain, the quantifier "the $\beta$-est" (and comparatives) is FOL-expressible


## Expressiveness: count $(\cdot), \operatorname{sum}(\cdot), \operatorname{prod}(\cdot)$

## Theorem

If we consider Rat $=(\mathbb{Q} ;+, \times ; \geq)$ (ordered field of the reals) to hold, then:
(1) $\operatorname{prod}(\cdot)$ and $\operatorname{avg}(\cdot)$ are definable in terms of $\operatorname{sum}(\cdot)$ and $\operatorname{count}(\cdot)$
(2) $\operatorname{sum}(\cdot)$ is definable in terms of count $(\cdot)$
(3) the quantifier "most" is definable in terms of "the number of"
$\triangleright$ Recall: $\llbracket$ most $\rrbracket=\{(A, B \subseteq \Delta \times \Delta \mid \operatorname{count}(A \cap B) \geq \operatorname{count}(A \backslash B)\}$

## Theorem

Aggregate quantifiers are not FOL-expressible
$\triangleright$ The generalized quantifier "most" is not FOL-expressible [BC80]


## Semantic Complexity [PH10]

## Definition (Semantic Complexity)

Given model $\mathcal{I}$, the semantic complexity of quantifier $Q$ expressible by $\bar{Q}(A, B)$ is defined as the cost of computing $\mathcal{I}, \gamma \models \bar{Q}(A, B)$, for some $\gamma \in \Delta^{F V(\bar{Q}(A, B))}$

- Computational cost $=$ computational complexity
- We measure cost only in $\#(\Delta)$ : data complexity
- If data complexity:
(1) is at most in P :
$Q$ tractable
(2) lies beyond P:
$Q$ intractable


## Remark

We consider the (simple) hierarchy: $\mathrm{AC}^{0} \subseteq \mathrm{~L} \subseteq \mathrm{P} \subseteq$ NP-complete $\subseteq \mathrm{NP}$


## Tractable Quantifier Complexity I

Quantifier

| some | $\mathrm{AC}^{0}$ |
| :---: | :---: |
| every | $\mathrm{AC}^{0}$ |
| at least $k$ | $\mathrm{AC}^{0}$ |
| more than $k$ | $\mathrm{AC}^{0}$ |
| exactly $k$ | $\mathrm{AC}^{0}$ |
| the $\alpha$-est | $\mathrm{AC}^{0}$ |


| the total $\alpha$ of | L |
| :---: | :--- |
| the number of | L |
| the average $\alpha$ of | L |
| the product $\alpha$ of | L |

$\begin{array}{cl}\text { most } & \mathrm{L} \\ \text { more than } p / k \text { of } & \mathrm{L}\end{array}$

## Tractable Quantifier Complexity II

Quantifier

| some | $\mathrm{AC}^{0}$ |
| :---: | :---: |
| every | $\mathrm{AC}^{0}$ |
| at least $k$ | $\mathrm{AC}^{0}$ |
| more than $k$ | $\mathrm{AC}^{0}$ |
| exactly $k$ | $\mathrm{AC}^{0}$ |
| the $\alpha$-est | $\mathrm{AC}^{0}$ |

$\Rightarrow$ Beyond FOL

| the total $\alpha$ of | L |
| :---: | :---: |
| the number of | L |
| the average $\alpha$ of | L |
| the product $\alpha$ of | L |
| most | L |
| more than $p / k$ of | L |

## Ramsey Quantifiers [Szy10]

## Definition (Ramseyfication)

The Ramseyfication of $Q$ of type $(1,1)$ is the quantifier of type $(1,2)$

$$
R_{Q}=\left\{(A, R) \subseteq \Delta \times \Delta^{2} \mid \text { exists } X \subseteq A \text { s.t. }(A, X) \in Q \text { and for all } x, y \in X,(x, y) \in R\right\}
$$

- "Says" that the $A \mathrm{~s}$ that fall under $Q$ are $R$-connected
- Are conveyed in English by the reciprocal NP "each other"
- Can be used to express graph properties such as the existence of cliques
- They are not FOL expressible



## Ramsey Quantifiers Example

more than one third of PMs sit next to each other

model $\mathcal{I}_{1}$

model $\mathcal{I}_{2}$

## Ramsey Quantifiers [Szy10] (ctd.)

## Quantifier

$$
\begin{gathered}
\text { some }+ \text { each other } \\
\text { every }+ \text { each other } \\
\text { exactly } k+\text { each other } \\
\text { most }+ \text { each other }
\end{gathered}
$$

at least $k+$ each other
at least $k+$ each other
more than $k+$ each other
more than $p / k$ of + each other
D.C.
$\square$
P
P
P
P
NP-complete* (P) NP-complete* (P) NP-complete* (P)

NP-complete

## Answer Time and Complexity [Szy09]



## Power Law Distributions [Bar09]

## Definition (Power law)

We say that a random variable $X$ of outcomes $x_{1}, \ldots, x_{k}$ follows a power law or Zipf distribution if $\leq 20 \%$ of its outcomes concentrate $\geq 80 \%$ of its probability mass. This relation is described by the equation:

$$
P(x) \sim \frac{b}{\operatorname{rank}(x)^{m}}
$$

- We want to know if quantifier distribution $P(Q)$ is power-law correlated to quantifier expressiveness/complexity:

$$
P(Q) \sim \frac{b}{\operatorname{comp}(Q)^{m}}
$$



## Power Law Example


(c)2006 Search Tools Consulting


## Corpora

| Corpus | Size | Domain | Type |
| :---: | :---: | :---: | :---: |
| Brown | 19,741 sentences | Open (news) | Declarative |
| Geoquery | 364 questions | Geographical | Interrogative |
| Clinical ques. | 12,189 questions | Clinical | Interrogative |
| TREC 2008 | 436 questions | Open | Interrogative |

## Remark

Corpora of different types and domains and approx. 1,000,000 words (cumulatively)

## Power Laws and Log-Log Regressions

- We can transform power laws to linear models via logarithmic scaling

$$
\begin{aligned}
y & =b / x^{m} \\
& \Leftrightarrow \\
\log _{10}(y) & =\log _{10}(b)-m \cdot \log _{10}(x)
\end{aligned}
$$

- We can estimate $b$ and $m$ from a sample $\mathcal{S}$ via linear regression
- If $R^{2}$ coefficient is high $\Rightarrow \mathcal{S}$ power law distributed



## Quantifier Distribution (all)

Distribution of GQs


Distribution of GQs (log-log best fit)


## Ramsey Quantifier Distribution

Distribution of Ramsey GQs


Distribution of Ramsey GQs (log-log best fit)



## Test Statistics

| skewness | Recip. GQs | GQs |
| :---: | :---: | :---: |
| skew. value | 1.76 | 1.98 |


| $\chi^{2}$-test | Recip. GQs | GQs |
| :---: | :---: | :---: |
| $\chi^{2}$ value | 530.81 | 183815415173.11 |
| $p$ value, d.f. | $1.78,5$ | $0.0, \quad 13$ |


| $R^{2}$-coeff. | Recip. GQs | GQs |
| :---: | :---: | :---: |
| Power law $\operatorname{fr}(Q)$ | $36.00 / r k(Q)^{0.82}$ | $2.88 / r k(Q)^{4.52}$ |
| $R^{2}$ coeff. | 0.47 | 0.81 |

## Remark

Power laws of mean relative frequency


## Conclusions

(1) We have studied the distribution of FOL, proportional and aggregate generalized quantifiers in corpora
(2) It may seem that their distributions is skewed towards low complexity quantifiers
(3) The skewed distribution is consistent with cognitive experiments [BSS11]
(4) We have considered if such distribution can be modeled by a power law

C. Thorne, J. Szymanik (KRDB, ILLC)

## Thank you :-)


http://www.inf.unibz.it/~cathorne

## References I

國 Marco Baroni．
Distributions in text．
In Mouton de Gruyter，editor，Corpus linguistics：An International Handbook， volume 2，pages 803－821． 2009.
John Barwise and Robin Cooper．
Generalized quantifiers and natural language．
Linguistics and Philosophy，4（2）：159－219， 1980.
Oliver Bott，Fabian Schlotterbeck，and Jakub Szymanik．
Interpreting tractable versus intractable reciprocal sentences．
In Proceedings of the 3rd Intenational Conference in Computational
Semantics（IWCS 2011）， 2011.
围 Ian Pratt－Hartmann．
Computational complexity in natural language．
In Handbook of Computational Linguistics and Natural Language Processing， chapter 2，pages 43－73．Wiley－Blackwell， 2010.

## References II

Jakub Szymanik.
Quantifiers in Time and Space.
Institute for Logic, Language and Computation, 2009.


Jakub Szymanik.
Computational complexity of polyadic lifts of generalized quantifiers in natural language.
Linguistics and Philosophy, 33(3):215-250, 2010.
围 Camilo Thorne.
Query Answering over Ontologies Using Controlled Natural Languages.
PhD thesis, Faculty of Computer Science, 2010.


## Aggregations [Tho10]

## Definition (Aggregation Function)

An aggregate function is a is a function that takes as argument a group $G$ and returns a number $n \in \mathbb{Q}$, viz.,

$$
\begin{array}{ccc}
\operatorname{count}(G) & \operatorname{sum}(G) & \operatorname{argmin}(G) \\
\operatorname{avg}(G) & \operatorname{prod}(G) & \operatorname{argmax}(G)
\end{array}
$$

- They require models with a ordered numerical domain $N \subseteq \Delta$, with $N$ a finite subset of $\mathbb{Q}$
- The argument group $G$ is built via, possibly, metric attributes $\beta(\cdot)$



## Tractable Quantifiers

## Theorem

The semantic (data) complexity of $F O L$ quantifiers is in $\mathrm{AC}^{0}$
$\triangleright$ Known result from FOL finite model theory

## Theorem

The semantic (data) complexity of aggregate quantifiers (and proportional quantifiers) is in L
$\triangleright$ One can design a sound an complete algorithm $\operatorname{Ans}_{\alpha}(\mathcal{I}, \bar{Q}(A, B))$ for solving $\mathcal{I} \models \bar{Q}(A, B)$ that runs in space $O(\log \#(\Delta))$

## Answering Aggregations $(O(\log \#(\Delta))$ Space)

```
procedure \(\operatorname{ANs}_{\alpha}(Q(\alpha(\beta(P))), \mathcal{I})\)
    \(\varphi(x)_{P} \leftarrow \operatorname{CORE}(Q(\alpha(\beta(P)))) ; \quad \triangleright\) compute core
    \(s \leftarrow 0 ; a \leftarrow 0 ; n \leftarrow 0 ; p \leftarrow 0 ; \quad \triangleright\) initialize
    for \(\gamma \in \operatorname{Sat}_{\mathcal{I}}(\varphi(x))\) do \(\triangleright \operatorname{Sat}_{\mathcal{I}}(\varphi(x))=\{\gamma \mid \mathcal{I}, \gamma \models \varphi(x)\}\)
        \(n \leftarrow n+1 ; s \leftarrow s+\beta(\gamma(x)) ; \quad \triangleright\) update 1
        \(a \leftarrow \frac{s}{n} ; p \leftarrow p \times \beta(\gamma(x)) ; \quad \quad \triangleright\) update 2
        if \(\alpha=\) count and \(Q(n)\) then \(\quad \triangleright\) test 1
            return true;
        else
            if \(\alpha=\mathbf{a v g}\) and \(Q(a)\) then \(\quad\) test 2
                return true;
            else
                if \(\alpha=\operatorname{sum}\) and \(Q(s)\) then \(\triangleright\) test 3
                    return true;
                else
                    if \(\alpha=\operatorname{prod}\) and \(Q(p)\) then \(\quad \triangleright\) test 4
                    return true;
                    end if
                    end if
                end if
        end if
        end for
        return false; \(\quad \triangleright\) false if all tests fail
: end procedure
```



## Linear Regression (Reminder)

A linear regression model has the form:

$$
Y=\Theta X
$$

with parameters $\Theta=(m, b)^{T}$ (a gradient and an intercept)

The least squares method infers from training sample $\mathcal{S}=\left\{\left(x_{i}, y_{i}\right)\right\}_{i \in[1, n]}$ the model whose parameters $\Theta^{*}$ :

$$
\Theta^{*}=\arg \min _{\Theta} J(\Theta)=\arg \min _{\Theta} \sum_{i=1}^{n}\left(y_{i}-\Theta\left(x_{i}\right)\right)^{2}
$$

minimize square error

The $R^{2}$ coefficient provides a measure of confidence in $Y=\Theta^{*} X$ :

$$
R^{2}=\frac{\operatorname{Var}\left(\Theta^{*} X\right)}{\operatorname{Var}(Y)}
$$



## Ramsey and non-Ramsey (raw)

| Corpus | $>k+$ <br> recip | $>p / k+$ <br> recip | most + <br> recip | ome + <br> recip | all + <br> recip | $k+$ <br> recip |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Brown | 1 | 1 | 2 | 2 | 2 | 16 |
| TREC | 0 | 0 | 0 | 0 | 0 | 0 |
| Geo | 0 | 0 | 0 | 0 | 0 | 0 |
| Clin. qs. | 0 | 0 | 0 | 0 | 0 | 0 |
| total | 1 | 1 | 2 | 2 | 2 | 16 |


| Corpus | $\geq k$ | $\leq k$ | most | $>k$ | $>p / k$ | recip. | $>k \%$ | sum | cnt | avg | max, min | all | $k$ | some |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Brown | 192 | 4 | 1532 | 540 | 38 | 101 | 2 | 1 | 354 | 17 | 4368 | 202587 | 90811 | 81693 |
| TREC | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 13 | 192 | 490 | 222 |
| Geo | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 18 | 380 | 447 | 660 |
| Clin. qs. | 12 | 0 | 28 | 12 | 0 | 0 | 0 | 0 | 9 | 2 | 889 | 10712 | 11629 | 20780 |
| total | 206 | 4 | 1560 | 552 | 38 | 101 | 2 | 1 | 364 | 19 | 5288 | 213871 | 103377 | 103355 |

