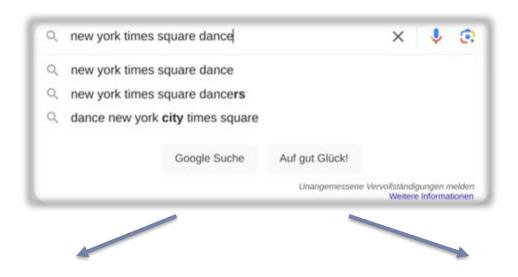
FRIEDRICH-SCHILLER-UNIVERSITÄT JENA

Johannes Franke

IR: Query Understanding WiSe 24/25

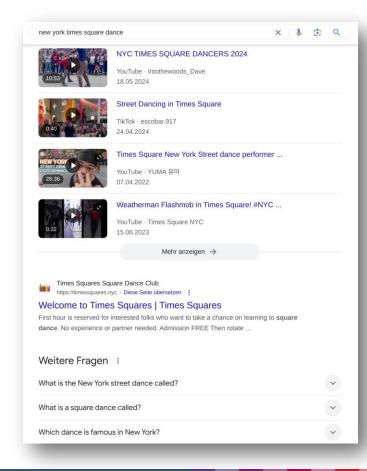
Query Segmentation

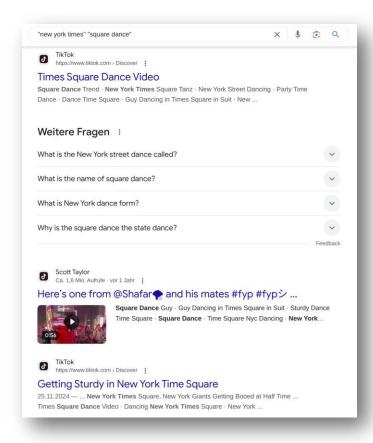
10.12.2024



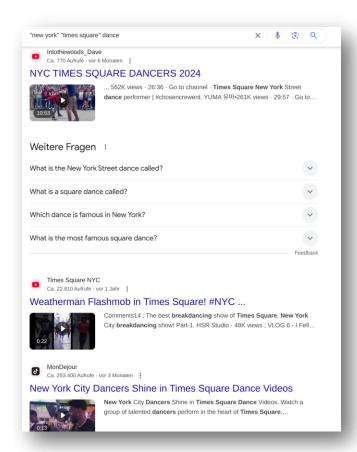
"new york" "times square" dance

"new york times" "square dance"



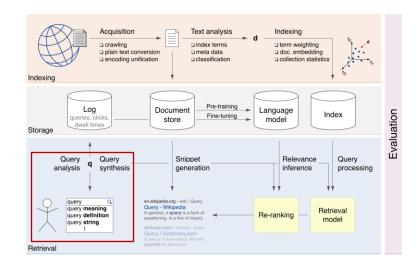






Grundlagen

- Aufteilung in Token-Sequenzen
- Query mit *n* Token hat *n* 1
 Breakpoints
- Segmentierungen haben Einfluss auf Bedeutung & Retrieval



Paper

- Query Segmentation for Web Search
 - Risvik et al., 2003
 - Publisher: The Web Conference

- Learning Noun Phrase Query Segmentation
 - Bergsma et al., 2007
 - Publisher: FMNI P-CoNI I (Empirical Methods in Natural Language Processing and Computational Natural Language Learning)

Learning Noun Phrase Query Segmentation

Shane Bergsma and Qin Iris Wang Department of Computing Science University of Alberta Edmonton, Alberta, Canada, T6G 2E8 {bergsma, wqin}@cs.ualberta.ca

Query Segmentation for Web Search

Knut Magne Risvik
Fast Search & Transfer ASA
PO, Box 4452 Hospitalslørkan
NO-7418 Trondfrøm, Norwey
D-80331 München, Germany

tomasz@fast.no

gines supporting inverse lookup of words and phrases. Data mining in query logs and document corpora is used to produce segment candidates and compute contextly measures. Candidates are con-sidered in correct of the whole query, and a list of the most likely segmentations is generated, with each segment attributed with a onnexity value. For each segmentation a segmentation acore in ortipated from connexity values of non-trivial segments, which an be used as a sorting criterion for the segmentations. We also point to a relevancy improvement in query evaluation model by means of proximity penalty.

1. INTRODUCTION

Web Search engines are rapidly emerging into the most impor-tant application of the World Wide Web. Several challenges arise when trying to make the web searchable[5]. Search engines like AllTheWeb[1], Google[3] and AltaVista[2]

are usually based on a kernel supporting inverse lookups of words and phrases. On top of these kernel features, techniques such as detection of proper phrases (e.g., new york — "new york") and removal of stopwords or stop-phrases (e.g. how can i get information

ner for a word-based or phrase-based inverse lookup, and thus improve precision of the search. For instance, a query like where can I find plaza hat in new york will most likely have better precision in a wendiphrase much intersection when rewritten into a form like "pizza hat" "new york". Problems with this query rewriting occur when there are ambi-

grities in phrasing and anti-phrasing alternatives. For instance the query free computer wallpaper downloads will be restitute into "free computer" wallpaper downloads if phrasing were done by a of more natural free "computer wallpaper" downloads.

In this paper we will describe how we use data mining in query logs and document corpora to derive information that can be used to seament overies into words and obcases with a number indicating

Copyright is held by the authoritemen(s). WWW,2003, May 25-24, 2003. Budapest, Hungary.

2. MINING LOGS AND CORPORA

Query logs yield a highly interesting data that may be useful for serious tasks. Whatever query coment specific application (statiotical merview, generation of related queries or triggering relevant flash-ins) is considered, a recognition of meaningful and normalis table phrases in each multiword query remains one of its core pre-

kens (words, numbers, special symbols) is considere meaningful phrase if the following conditions hold:

1. S is significantly frequent in all resources. $2.\,\,S$ has a 'good' mutual information.

Both above conditions make up a central notion for the seg-

mentation of queries, a connectly of a sequence $S=w_1\dots w_n$, which is defined as a product of the global frequency of the segment freq(S) and the mutual information I between longest but complete subsequences of S.

 $conn(S) = freq(S) \cdot I(w_1 ... w_{n-1}, w_2 ... w_n)$ (1) It is assumed that consexity of a single token is equivalent to its frequency i.e. $conn(ar_1) = freq(w_1)$ The connexity value presented here is computed from a selected sample of our query logs whose characteristics is: approx. 600 million original query lines and 105 million lines in its normalized frequency lise $Q_{\rm newalton}$. Most of the operations related to

the computation of connexity are carried out on O terration or on its into subsets according to the number of tokens in a line. Table 1 shows how many lines each subset of $Q_{norming}$ comists of and how many new (not seen in other subsets) segments $S = \omega_1 \dots \omega_n$

is estimated to $|S_{1234}| \simeq 144 \cdot 10^6$. A manageable subset $S_{1234} = S_{1234} = S$

Query processing speed ≥ 5000 queries/second,

. disk accesses excluded - full database that mass the sea-

be matched on a web cample, Zhai (1997) ngle-word symbols is h for "bank terminoley bank" The mader arrent search engine g does recognize the taning in some way. semantics also de ships between the number of possible d these can be exerent segmentations

tion marks around the earch engine to only ages about the large saws used by lumtrees, then the first ed, a phrasal search Google does find the second interpretarelevant pages dis-"nen-man handsaw.



Query Segmentation for Web Search

- Segmente = Bedeutungsvolle Phrasen mit
 - signifikanter Frequenz im Corpus
 - hoher "Mutual Information"

$$conn(S) = freq(S) \cdot I(w_1 \dots w_{n-1}, w_2 \dots w_n)$$

- Berechnung des Connexity-Scores für alle 2ⁿ⁻¹ Segmentierungen
- Sortierung nach max. kumulativen Scores

Query Segmentation for Web Search

$$conn(S) = freq(S) \cdot I(w_1 ... w_{n-1}, w_2 ... w_n)$$

S_1 = "new york" "times square" dance

- freq("new york") = 7.500
- freq("times square") = 100
- I("new", "york") = 0.04
- I("times", "square") = 0.02

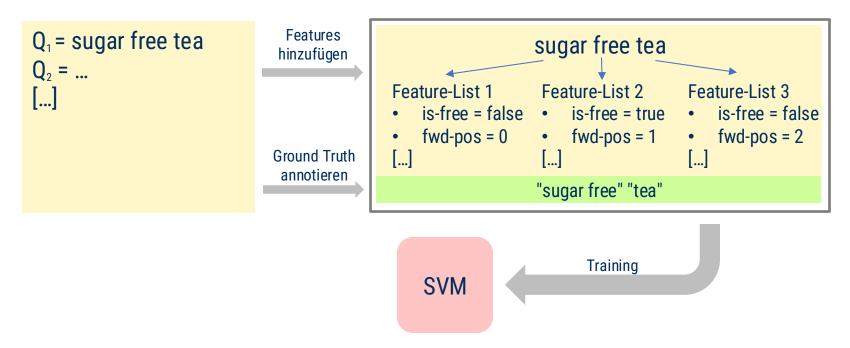
Score(
$$S_1$$
) = conn("new york") + conn("times square")
= 300 + 2
= 302

S₂ = "new york times" "square dance"

- freg("new york times") = 3.400
- freq("square dance") = 200
- I("new york", "york times") = 0.03
- I("square", "dance") = 0.01

- Segmentation als Classification Task mittels
 - supervised Machine Learning
 - Support Vector Model (SVM)
- Trennung wird an jedem Breakpoint einer Query entschieden
- Einbezug des Kontext in Form eines Token-Fensters
 - 3 Token links/rechts von Breakpoint (falls vorhanden)
 - genannt "Decision Boundary"

$$\{..., w_{L2}, w_{L1}, w_{L0}, w_{R0}, w_{R1}, w_{R2}, ...\}$$



Eingabe Segmentierung Q = new york times square dance SVM new york times square dance Trennung? Nein Ja Nein Ja "new york" "times square" dance



Annotation

- Aufteilung in Training, Validation und Test (je 500 Queries)
- "Ground Truth" von 3 Annotatoren manuell erstellt
- Agreement $\kappa = 0.69$

Naive Baselines

Ansatz	SegAcc.	QryAcc.
"always split"	0.44	0.04
"never split"	0.55	0.04



Decision Boundary

- Features für x_{L0} , x_{R0}
- Aufgeteilt in
 - Indikator F.
 - Statistische F.

Context

- Wie Decision Boundary
- Features für ganzes Fenster $x_{1,2}$ bis $x_{R,2}$

Dependency

- Nimmt Rücksicht auf Einfluss zwischen entfernten Token
- Count von
 - x_{L0} und x_{R1}
 - x_{L1} und x_{R0}

Indikator	Beschreibung
is-free	Token x = "free"
fwd-pos	Position von Anfang
rev-pos	Position von Ende
[]	

Statistik	Beschreibung
web-count	Häuf. von x im Web
Qcount-1	Häuf. von x in Query-Log
[]	

Feature Type	Feature Span	SegAcc.	QryAcc.
MI	Decision Boundary	0.68	0.26
Basic	Decision Boundary	0.71	0.29
Basic	Decision Boundary, Context	0.80	0.52
Basic	Decision Boundary, Context, Dependency	0.81	0.53
All	Decision Boundary	0.84	0.57
All	Decision Boundary, Context	0.86	0.63
All	Decision Boundary, Context, Dependency	0.85	0.61



Takeaways & Fragen

- Query Segmentation: Grundlagen & Motivation
- Connexity-Score: Bedeutung & Berechnung
- Segmentation als Classification-Task
- Feature-Engineering und Training eines SVMs

Dankeschön!



Mutual Information

$$\mathrm{I}(X;Y) = \sum_{y \in \mathcal{Y}} \sum_{x \in \mathcal{X}} P_{(X,Y)}(x,y) \log \Biggl(rac{P_{(X,Y)}(x,y)}{P_X(x)\,P_Y(y)}\Biggr)$$

$$\Leftrightarrow \log C(x_{L0}x_{R0}) + \log K - \log C(x_{L0}) - \log C(x_{R0})$$

- Ein Maß für die gegenseitige Abhängigkeit zweier Variablen
- Auch bekannt als "Information Gain"
- Benötigte Größen im IR Kontext:
 - rel. Wahrscheinlichkeiten von Token "x", "y" separat &
 - rel. Wahrscheinlichkeit von Token "x y" zusammen



Support Vector Machine (SVM)

- Überwachter, feature-basierter Klassifikationsalgorithmus
- Gilt für viele Probleme als guter Default-Ansatz
- Maximiert den Abstand zwischen den Trainingsinstanzen
 - Margin: max. Abstand zwischen Support Vectoren
 - Support Vectoren:
 Trainingsinstanzen am nächsten zur Margin

