

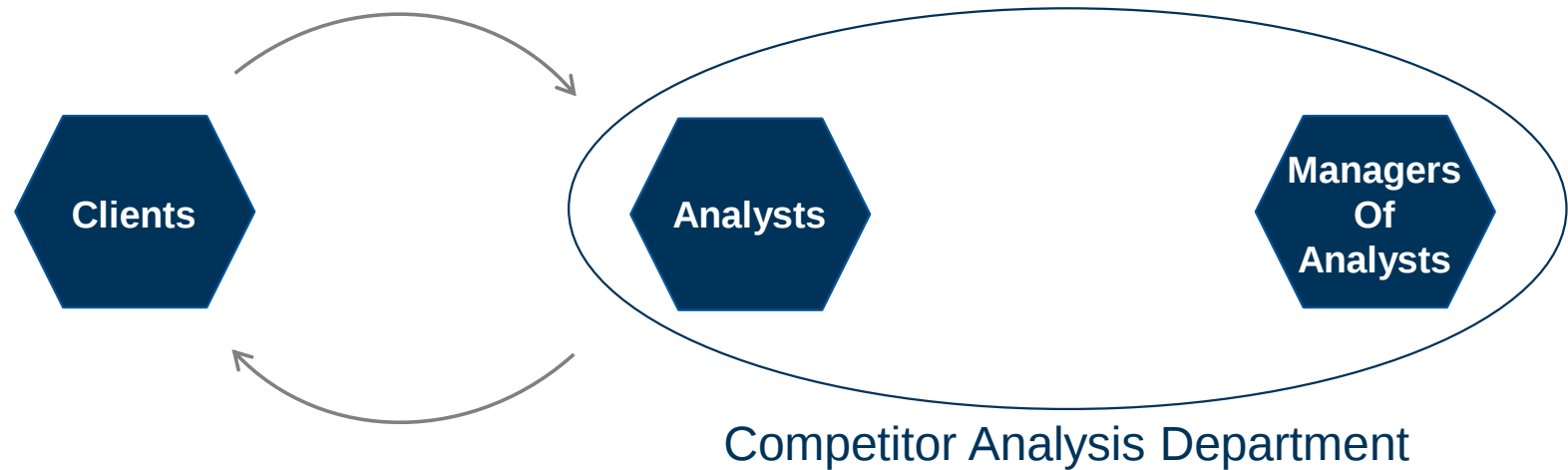
A Machine Learning based approach for the Competitor Information Analysis in the Automotive Industry

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Introduction

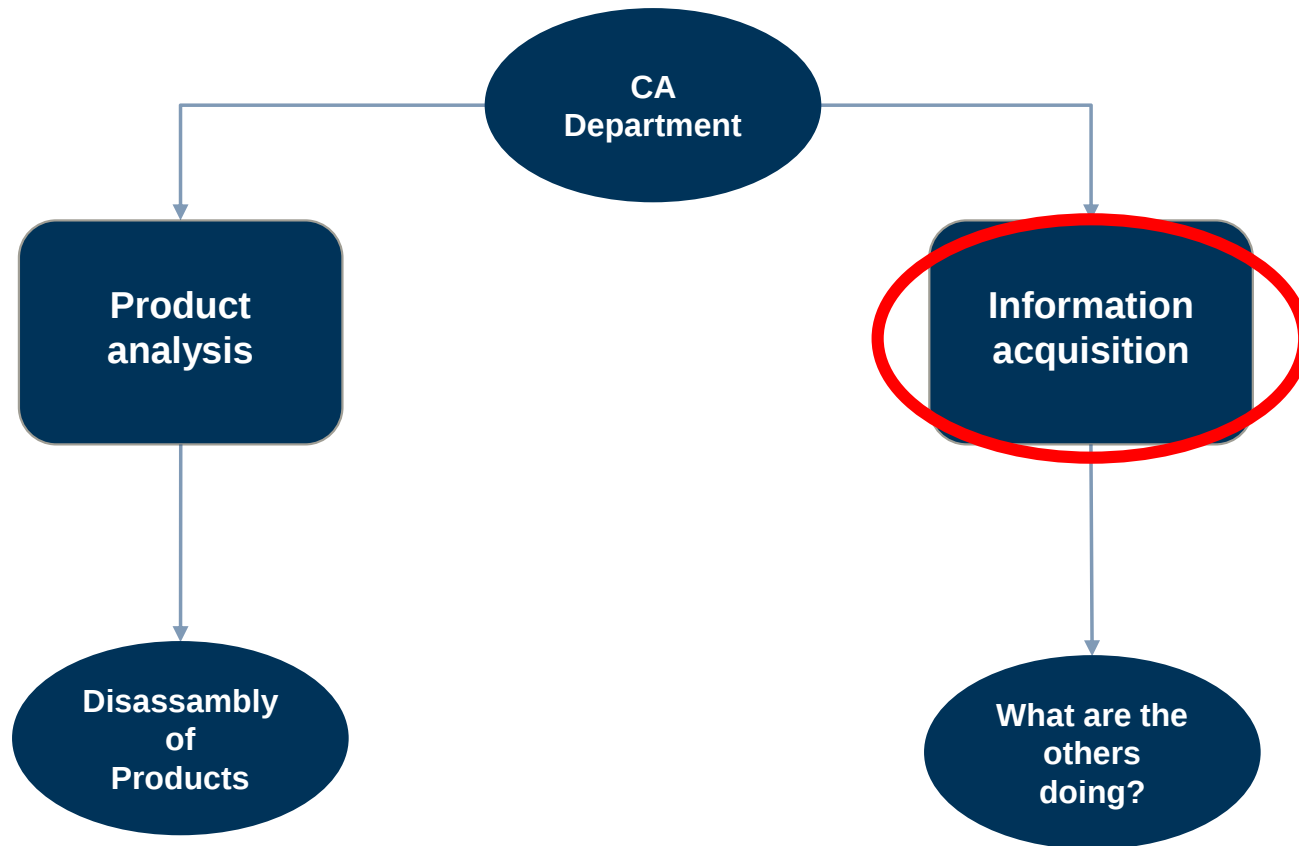
Competitor Analysis (CA) - Roles



Source: Organizing Competitor Analysis Systems, S.Ghoshal, E. Westney

Introduction

Competitor Analysis (CA) - Tasks



Motivation: Information acquisition

What kind of information?

- Not only about cars
- New technologies, interior design (furniture), materials, IoT, Smartphones,...

Employees search for information on the **internet**

- Newsfeeds
- Social Networks
- Patent databases
- Search engines

Problem

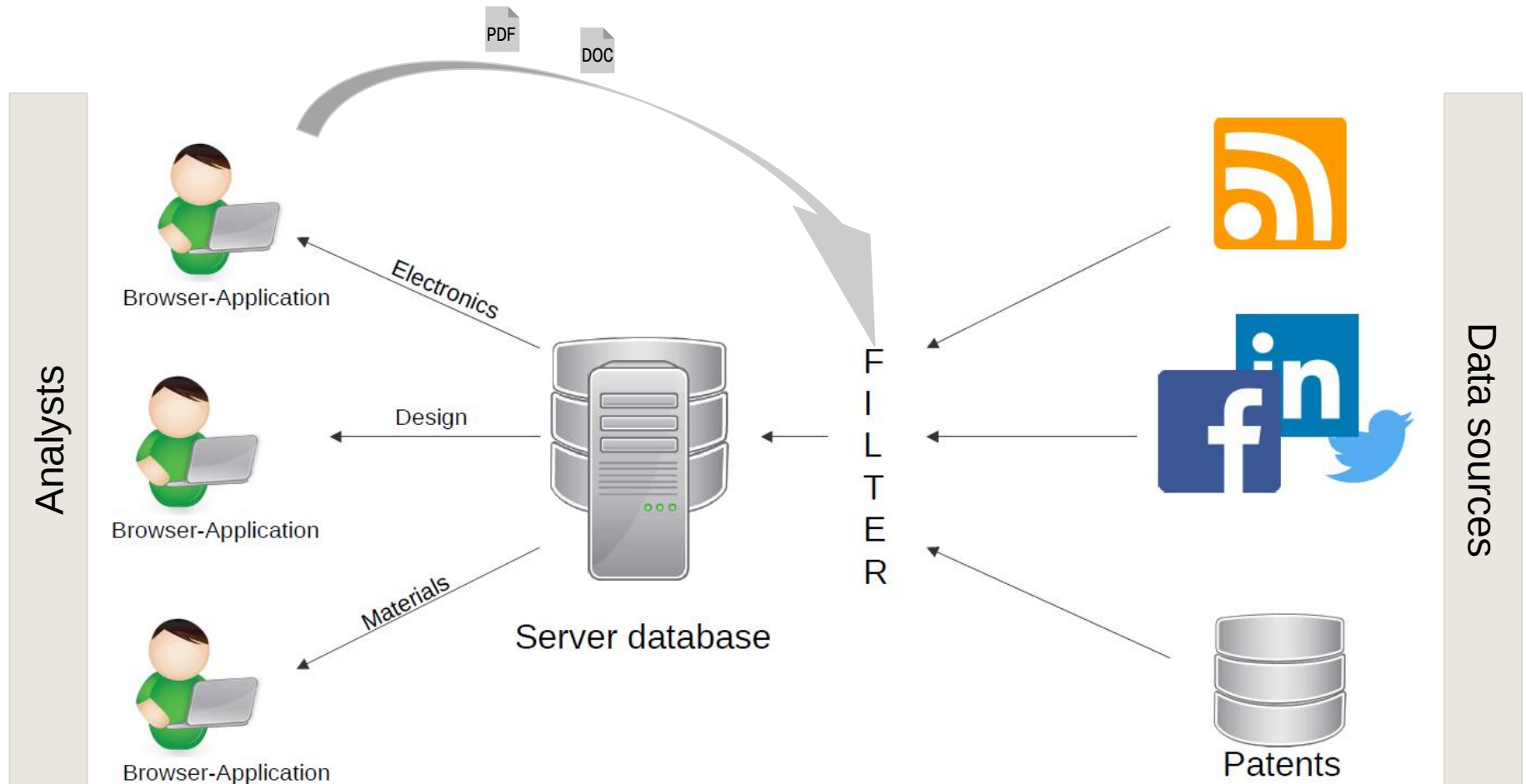
- ~ 40 Employees
- 2 hrs. per day

Research Questions

- How to improve the existing competitor information analysis process in the automotive domain?
- What kind of **documents** and document **sources** are used for competitor information analysis in the automotive domain?
- Which categories/topics do these documents belong to?
- Which machine learning algorithm performs best for automatic classification of documents to support competitor information analysis in the automotive domain?

Introduction

Information acquisition



- Comparison of available competitive analysis tools
- User analysis and requirements elicitation at the competitor analysis department
- Mockup design
- Collect sample documents
- Identifying topics for classification
- Manual classification of documents
- Create pipeline for automatic classification
- Analysis of results
- Implement/use server-side **document-management system** for classifying and storing document
- Implement a client application to search, retrieve, and view documents
- Evaluate the system at BMW

Tool Comparison

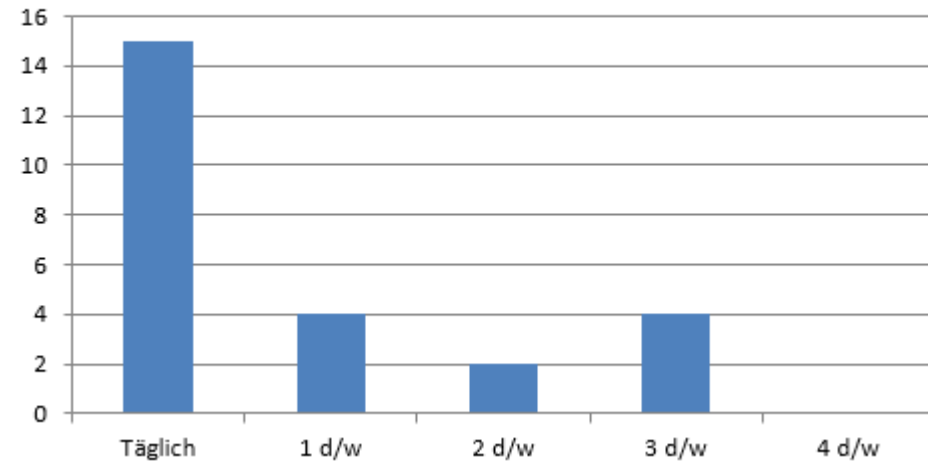
	Keyword mentions	Ad monitoring	backlinks	Social media	Company documents	Newsfeeds	Patents
Topsy	1	0	0	1	0	0	0
The Search Monitor	1	1	0	1	0	1	0
Socialmention	1	0	0	1	0	0	0
Majestic SEO	0	0	1	0	0	0	0
Infinigraph	0	0	0	1	0	0	0
Google Alerts	1	0	0	0	0	0	0

 CA relevant

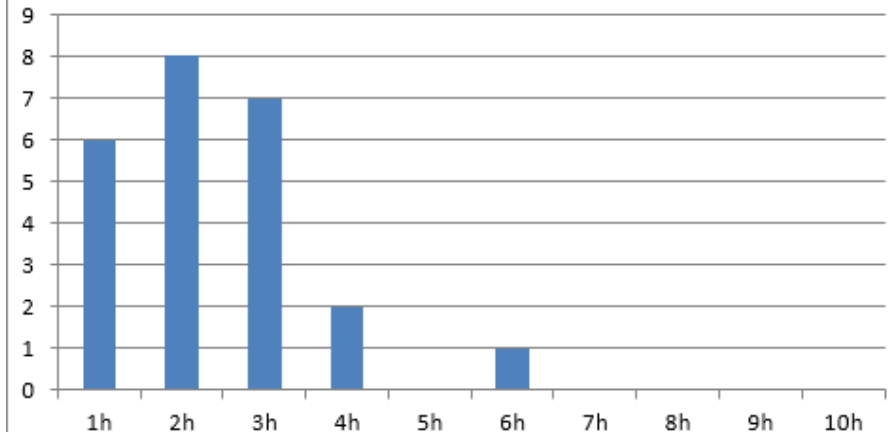
 CA irrelevant

User Analysis (1)

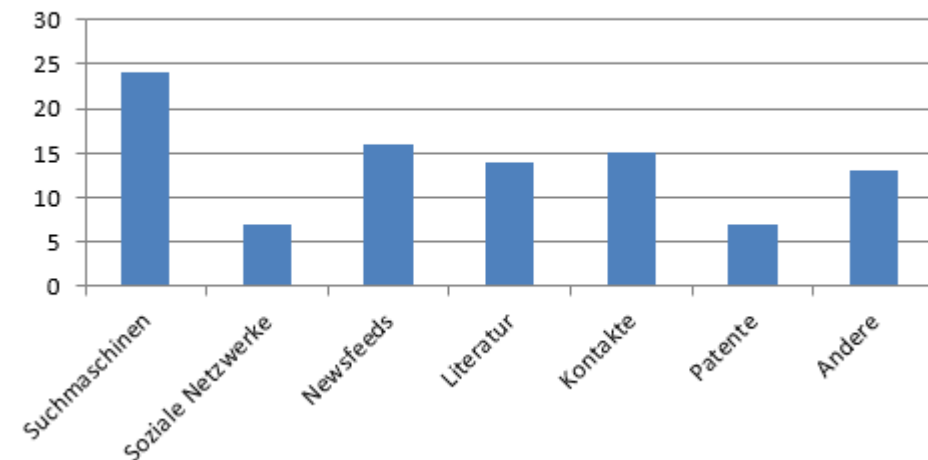
Häufigkeit der Recherche



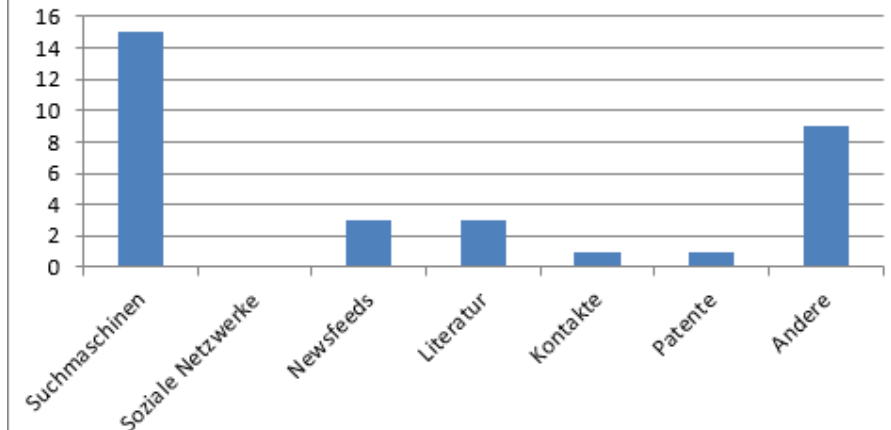
Dauer der Recherche pro Tag



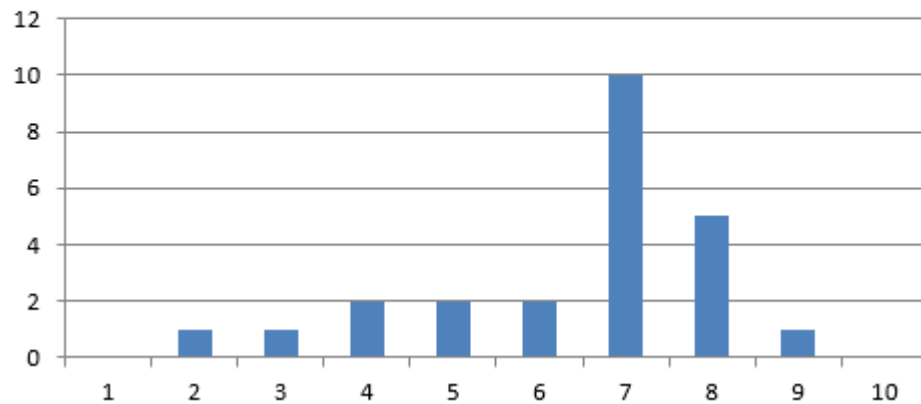
verwendete Quellen



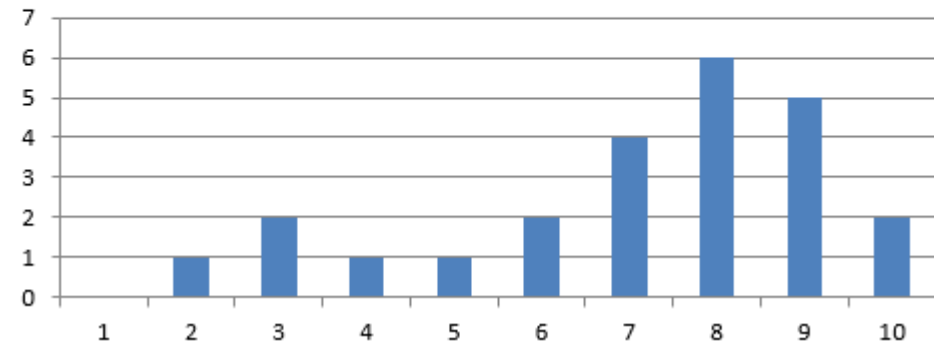
Häufigste Quelle



Wie effizient ist Ihre Methode zur Informationsakquise?



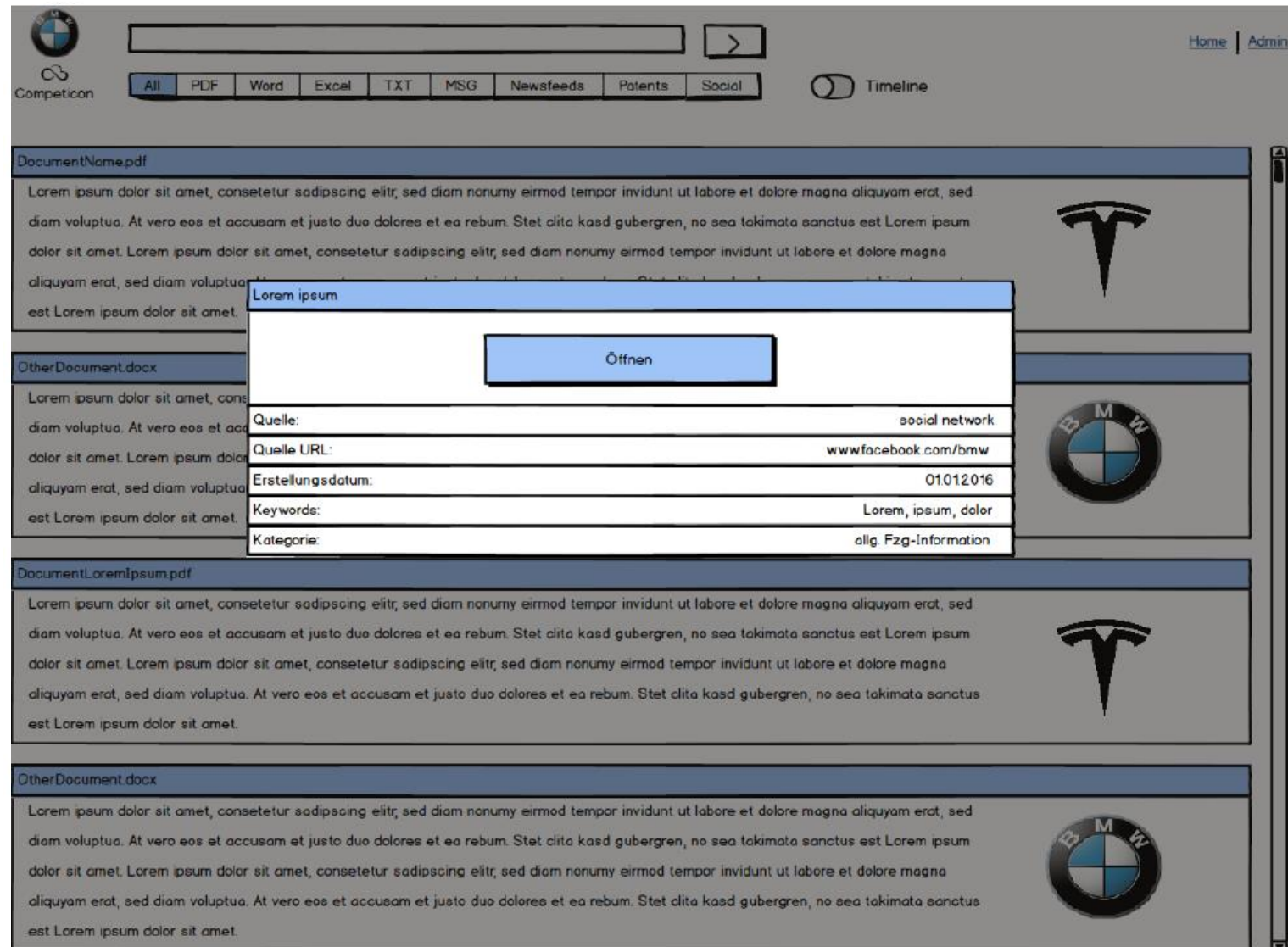
Wie oft stoßen Sie während der Recherche auf irrelevante Informationen?



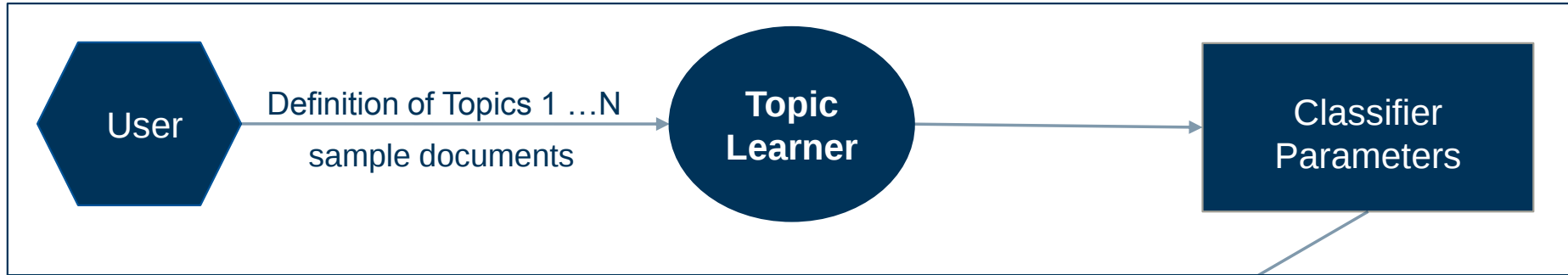
Mockups (1)



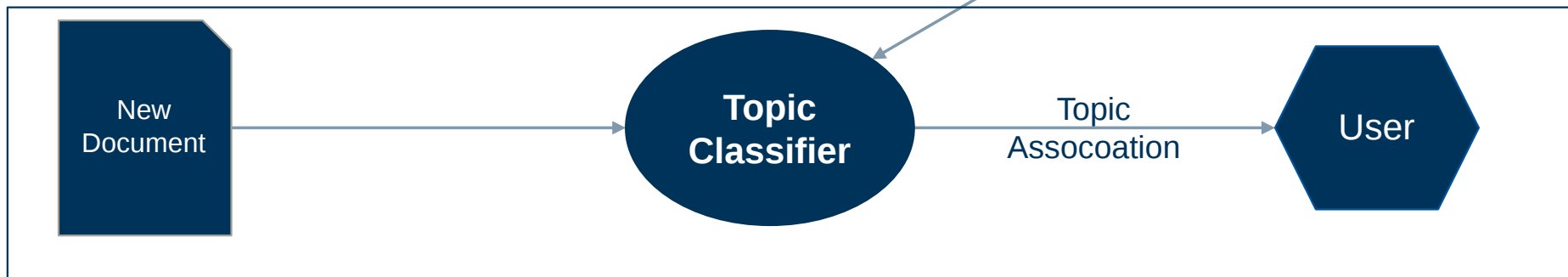
Mockups (2)



Learning Phase



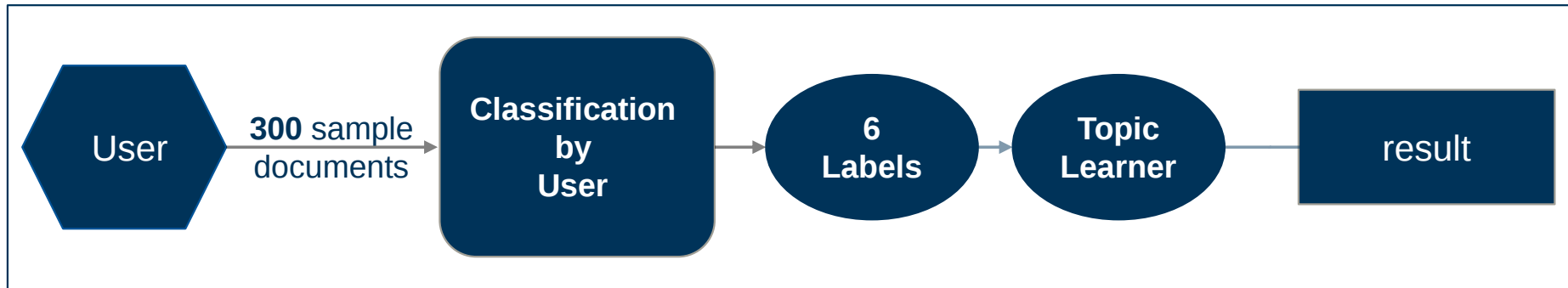
Classification Phase



Source: Automatic Document Classification: A thorough Evaluation of various Methods, C. Goller¹, J. Löning², T. Will¹, W. Wolff²

Learning phase

- Sample documents sorted by document patterns
- One document belongs to one label



Automatic Document Classification

Initial results of automatic classification

Classification	accuracy	Ø precision	Ø recall
kNN	91,28 %	88,12 %	85 %
Naive Bayes	92,77 %	89,46 %	88,02 %
1-vs-All	47,66 %	7,94 %	16,67 %

Tool support for competitor information analysis

Technology stack

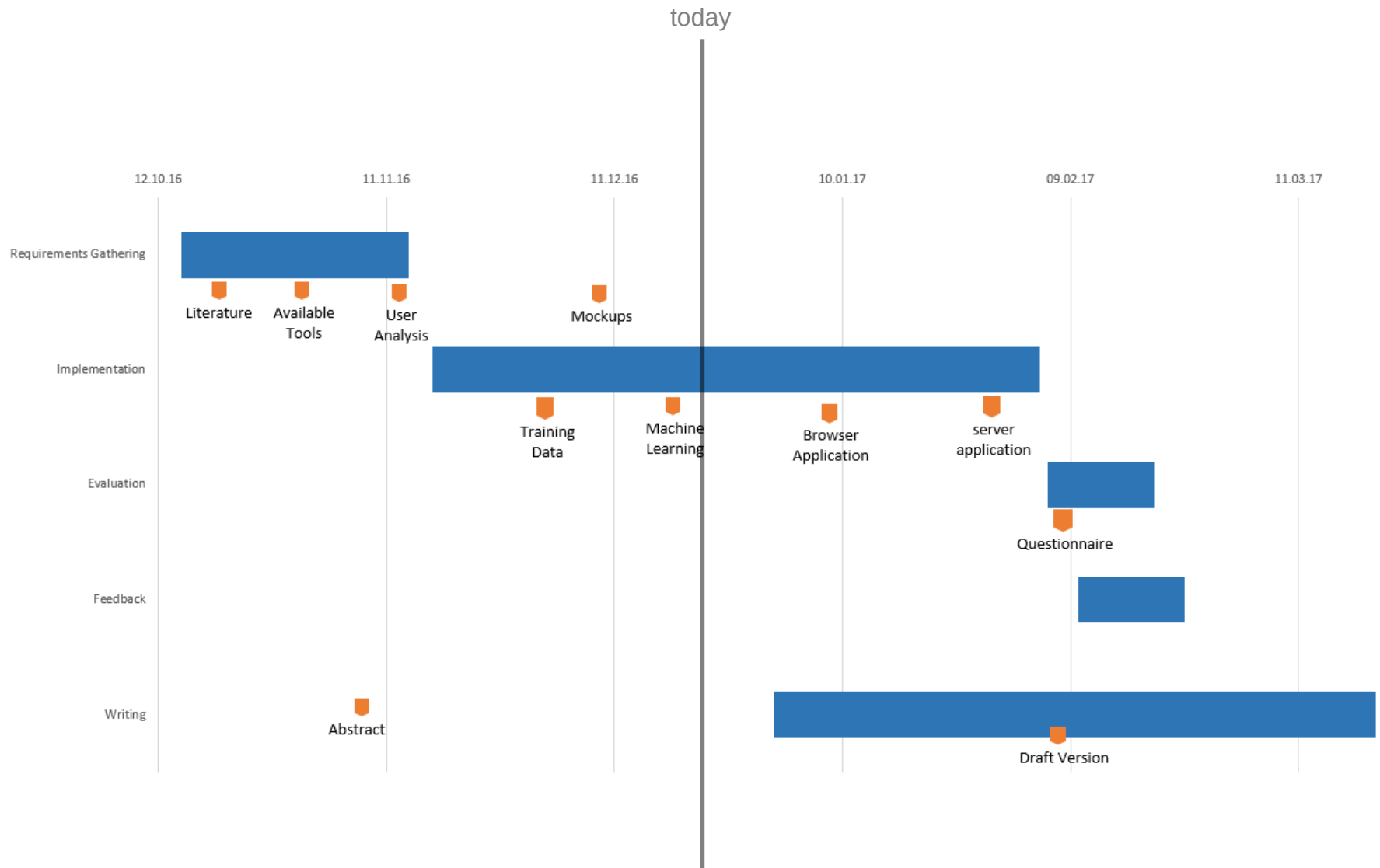
Client



Server



Road Plan





B.Eng.

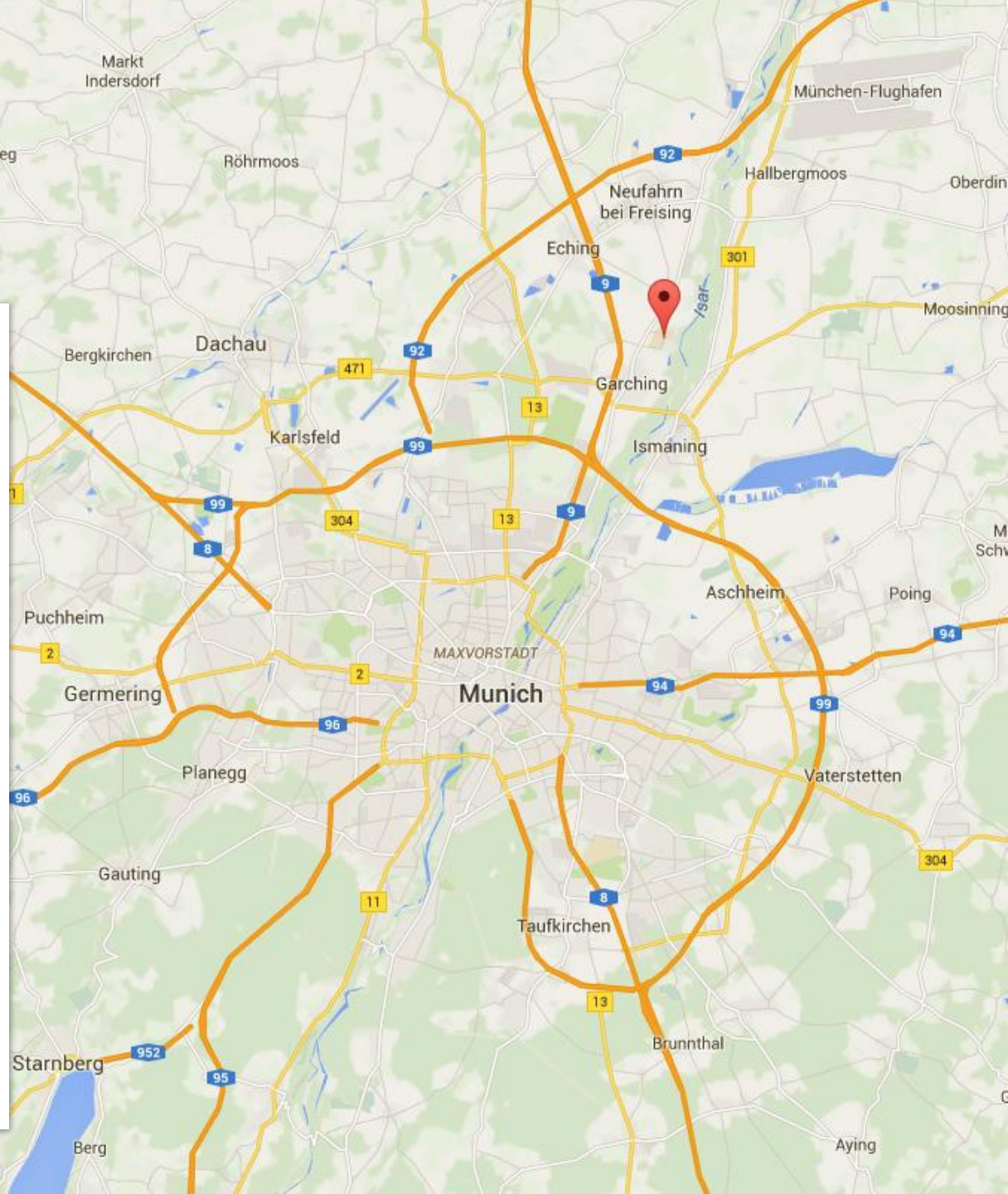
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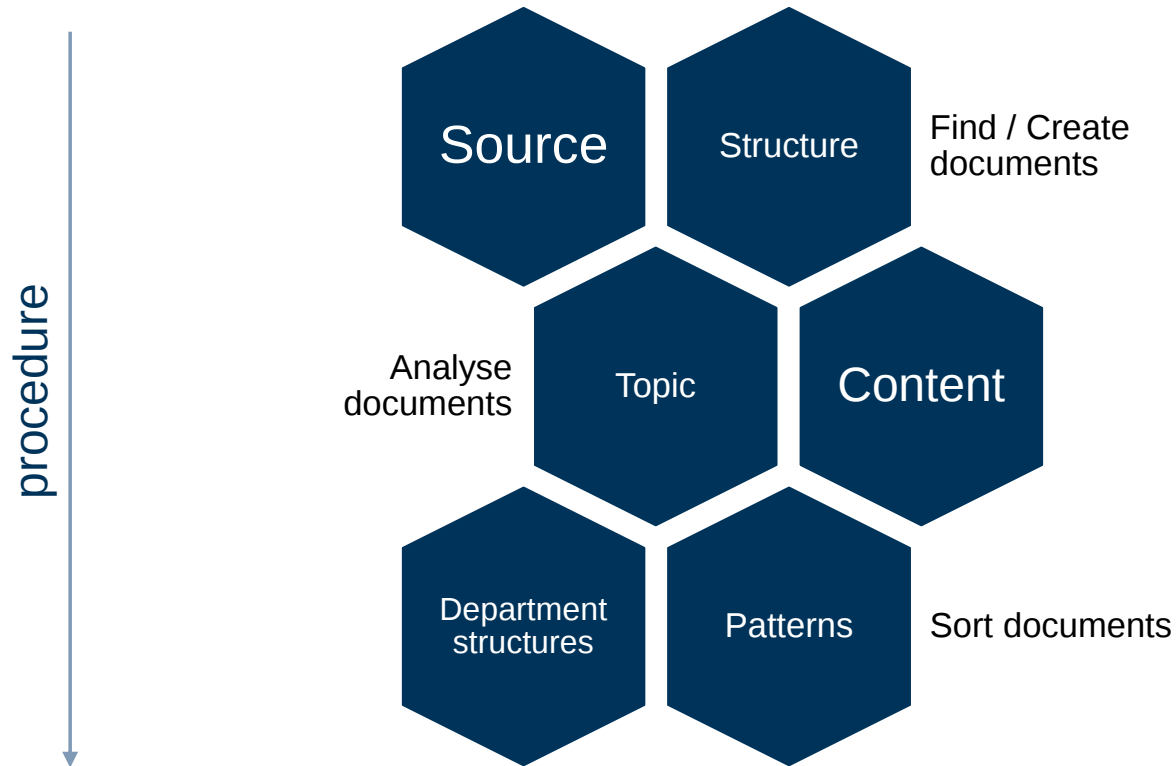
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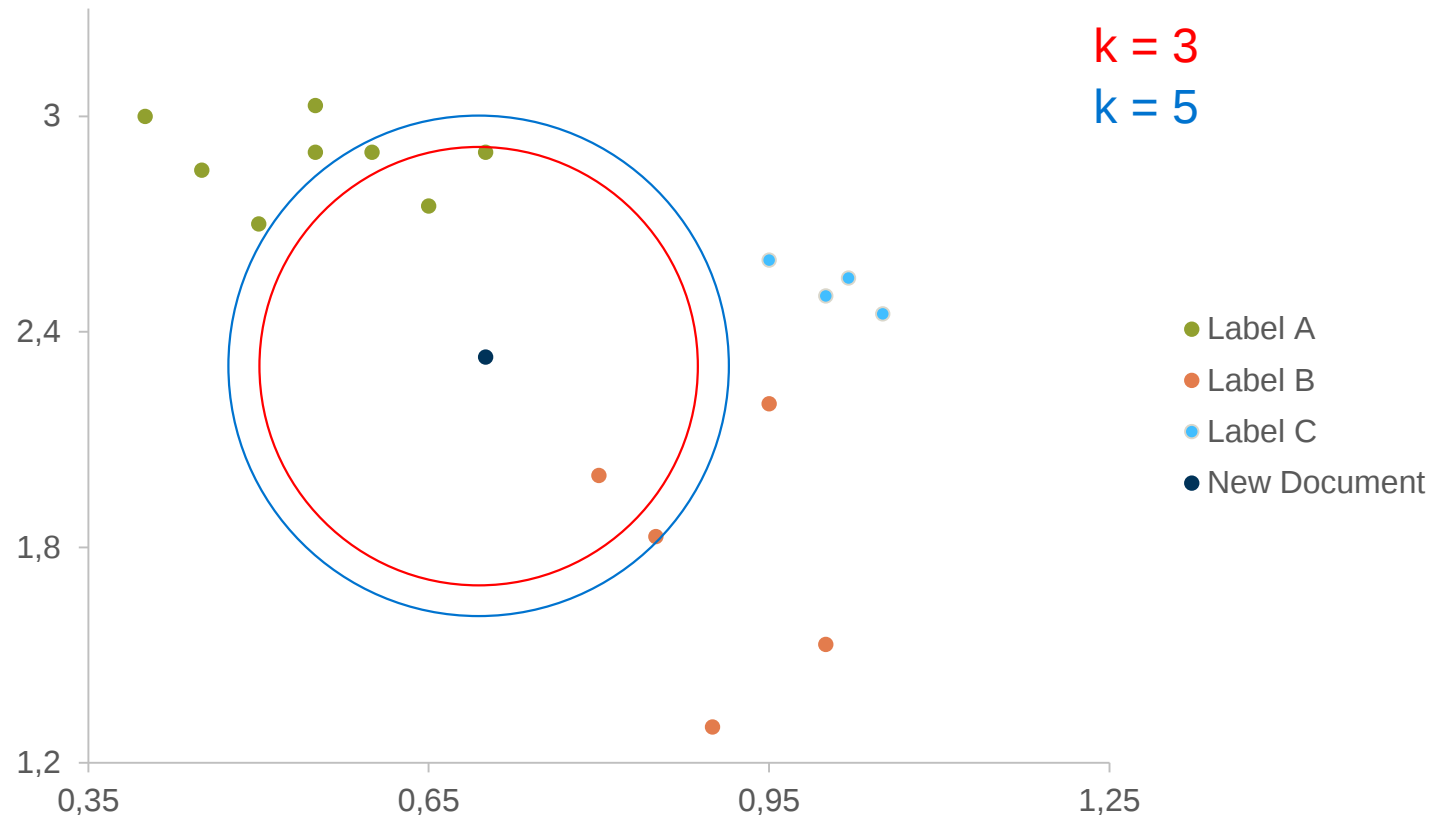


Backup-Slides

Document Preparation



K-Nearest Neighbor



Naive Bayes

Sunny	Temperature	Exams	Swim
Yes	Hot	No	True
Yes	Warm	Yes	False
No	Yes	No	True
Yes	Cold	Yes	False
Yes	Cold	No	False

Naive Bayes

Combination	Count
Sunny-Swim	11
Not Sunny-Swim	7
Cold-Swim	2
Warm-Swim	12
Hot-Swim	15
Exams-Swim	2
noExams-Swim	11

Combination	Count
Sunny-NoSwim	5
Not Sunny-NoSwim	6
Cold-NoSwim	11
Warm-NoSwim	4
Hot-NoSwim	3
Exams-NoSwim	10
noExams-NoSwim	2

Let's say we have a sunny, warm day and it's exam-time

$P(\text{swim} \mid \text{sun, weather, exams}) = P(\text{swim} \mid \text{sun})P(\text{swim} \mid \text{weather}) P(\text{swim} \mid \text{exams})$.

$P(\text{swim} \mid \text{sun, weather, exams}) = 11 \cdot 12 \cdot 2 / 60 = 288 / 60 = \mathbf{4,4}$

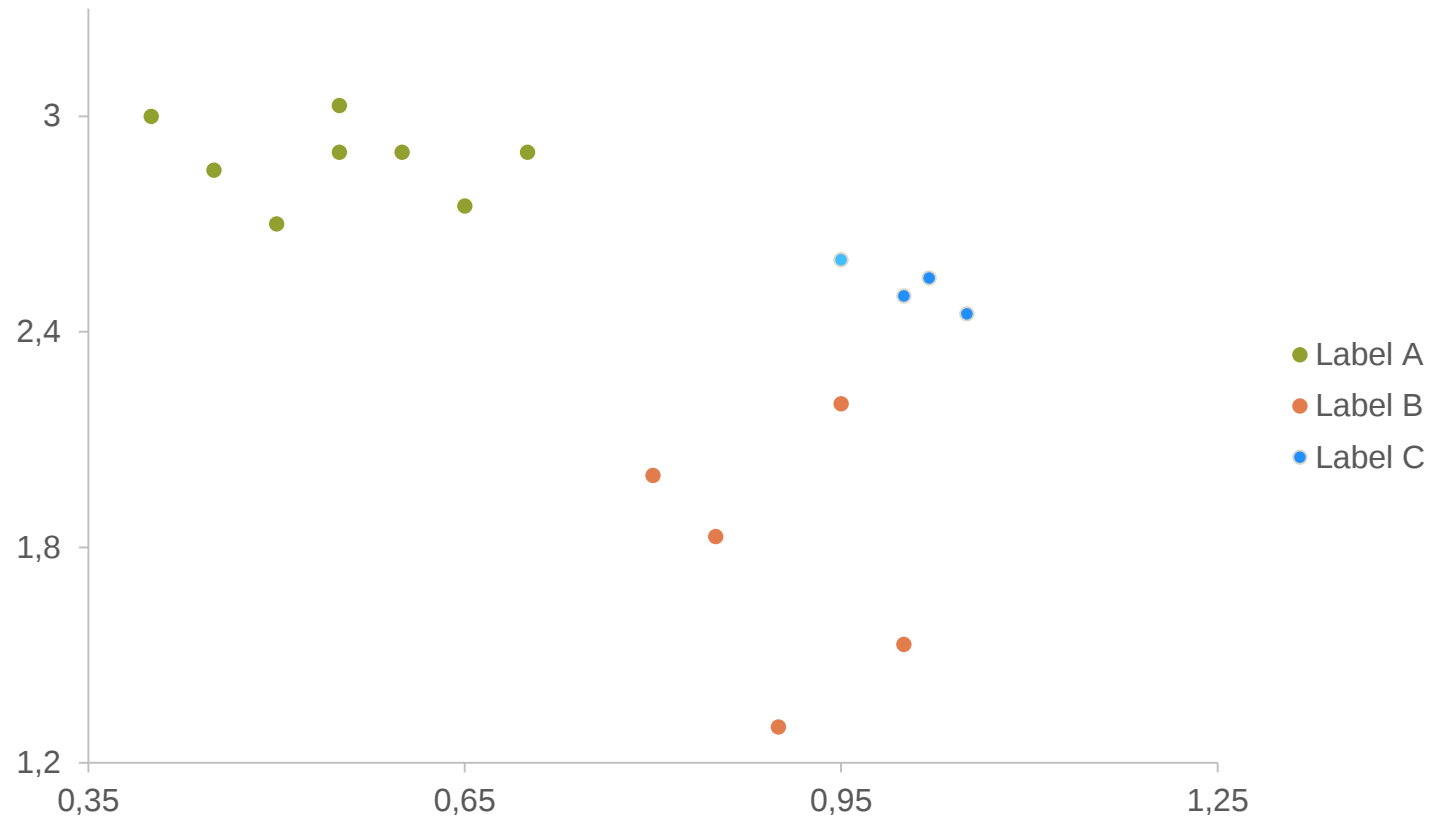
$P(\text{noSwim} \mid \text{sun, weather, exams}) = P(\text{noSwim} \mid \text{sun})P(\text{noSwim} \mid \text{weather}) P(\text{noSwim} \mid \text{exams})$.

$P(\text{noSwim} \mid \text{sun, weather, exams}) = 5 \cdot 4 \cdot 10 / 28 = 380 / 41 = \mathbf{7,14}$

➤ $P(\text{noSwim}) > P(\text{swim})$

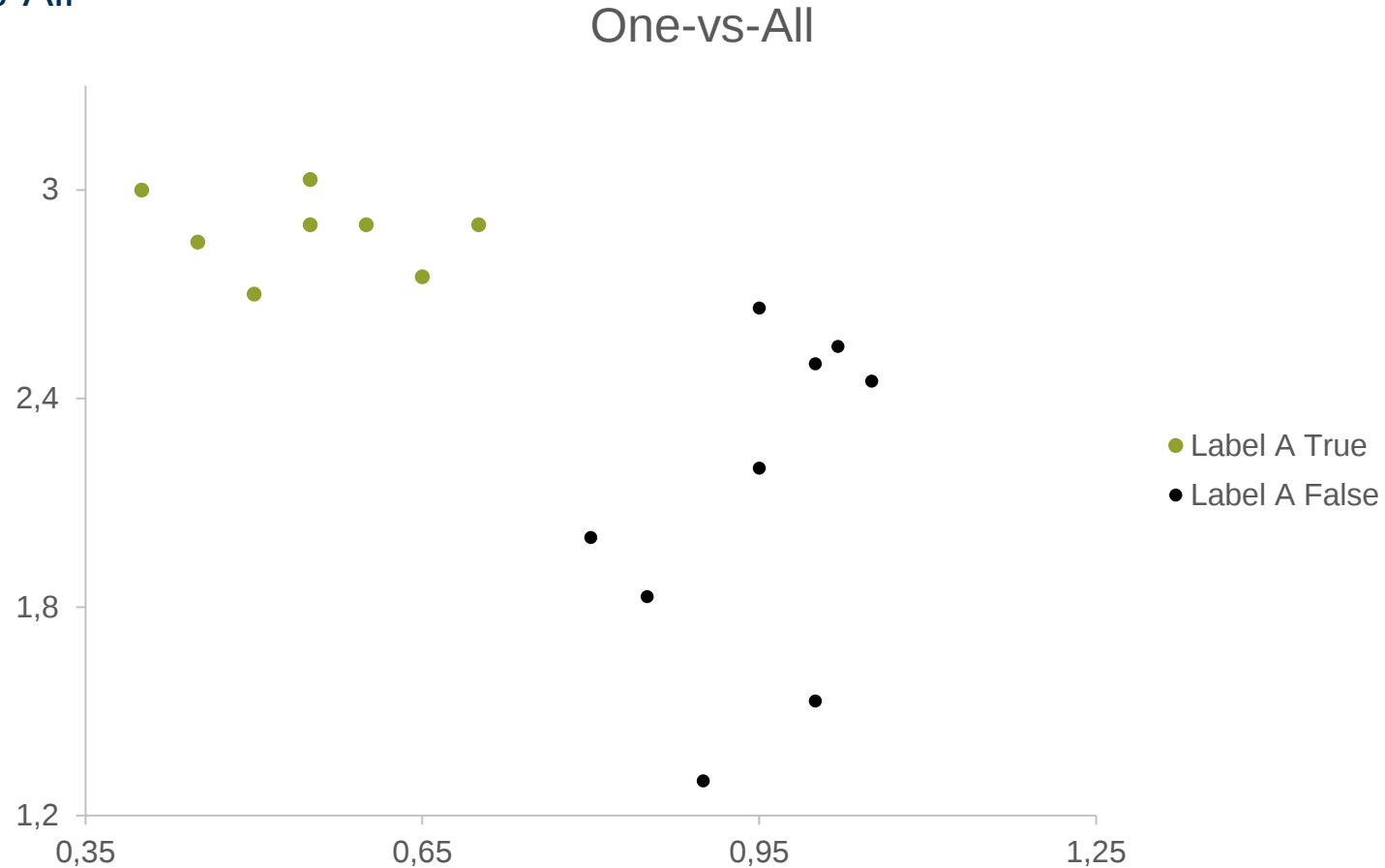
One-vs-All

One-vs-All



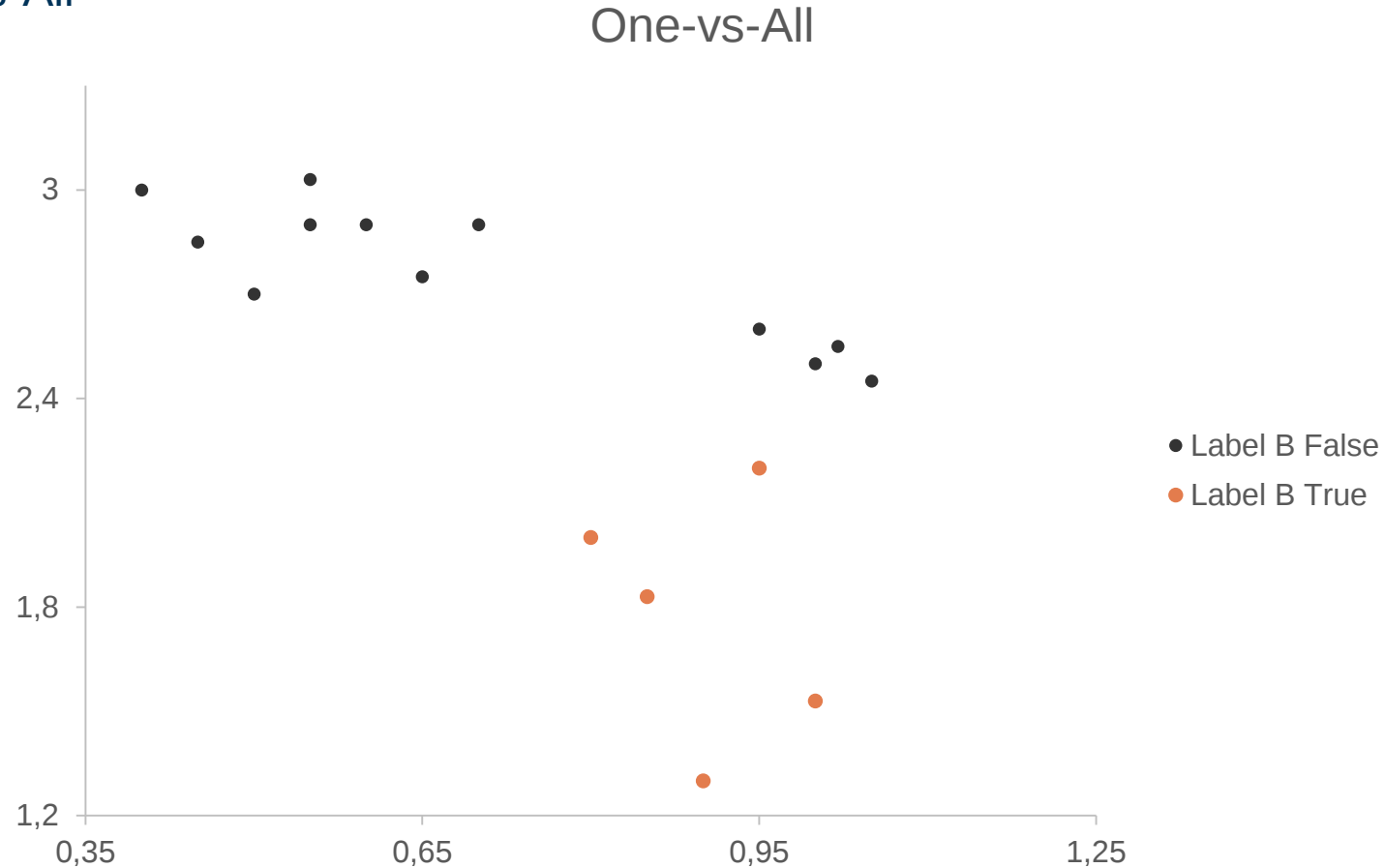
-> Divide in 3 binary classifications

One-vs-All



-> Divide in 3 binary classifications

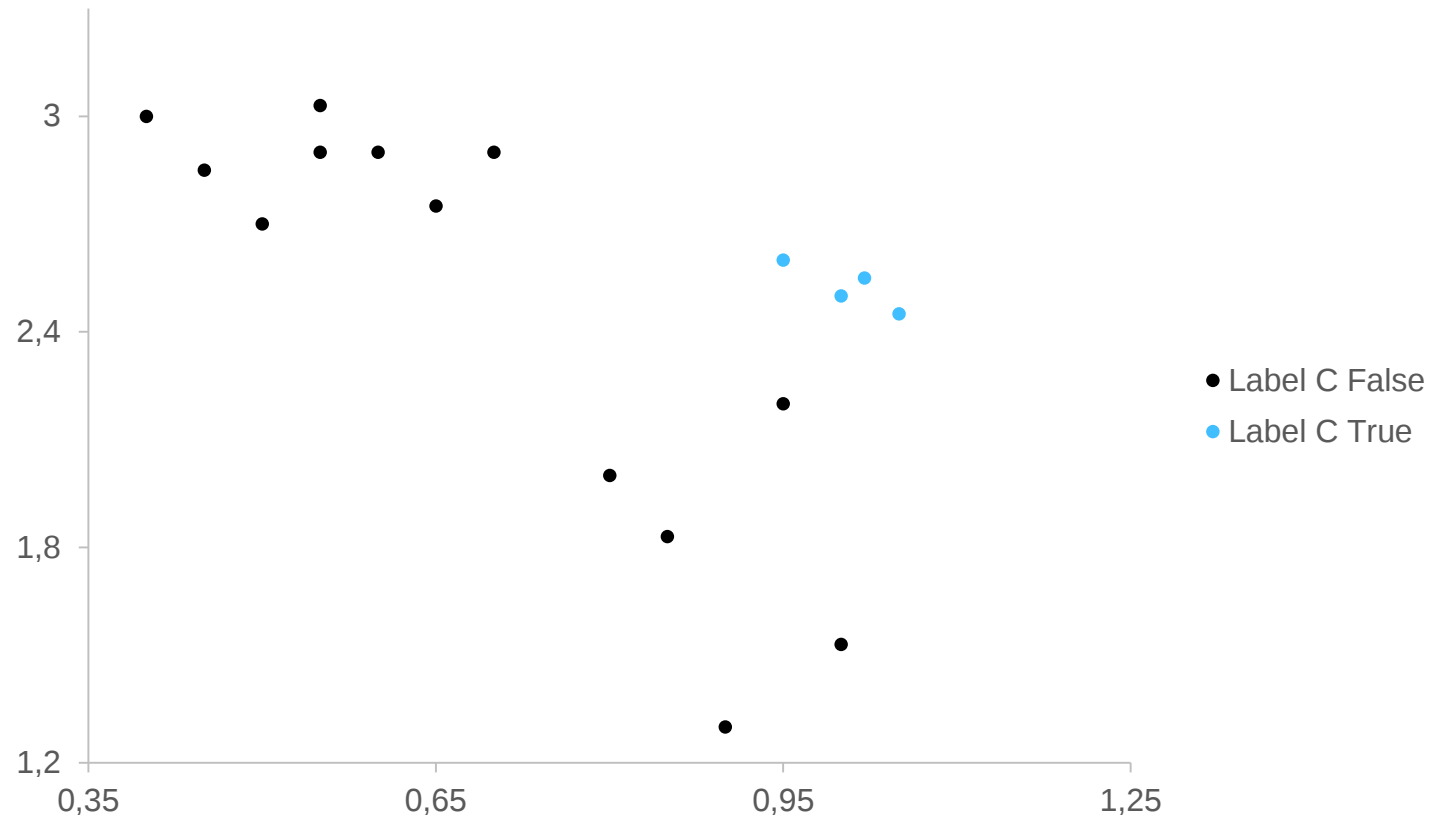
One-vs-All



-> Divide in 3 binary classifications

One-vs-All

One-vs-All



-> Devide in 3 binary classifications