# Job Recommendations at XING

Data Science Portugal Meet-up, Porto, 14<sup>th</sup> May 2018

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#### **Outline**

- Challenges and Algorithms
- Building Recommender Systems
- Deployment of RecSys Models
- Q&A



# RecSys Challenges and Algorithms







My contacts

My messages

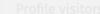
My Premium

My Projobs

Jobs Jobs

• Other services









Psychologie





Spread the word

Quality Assurance Manager

Share a link or post with your contacts

Members you may know

start page

≗+ Add

days



#### Also on XING:



ž°

2 Xing, AG

Melissa Lang



♣+ Add



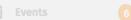


My contacts

My Premium

My Projobs





• Other services

#### XING Jobs

# jobs market

Overview Bookmarks (0) Search alerts (0) Jobs offering over €50,000

#### Jobs we think you'll like

Rate recommendations



#### Data Scientist/Machine Learning -Darmstadt - 75.000€

Senior Data Scientist Automotive & Manufacturing Industry (m/w)

T-Systems International GmbH, Berlin

Optimus Search, Darmstadt 13 days ago

00 68% match

Ţ..

11 days ago

① 71% match

#### SAP

#### Senior Developer / Development Expert for Machine Learning Platform Job

SAP, Berlin 13 days ago

74% match

#### Michael Page

#### Tech Lead Manager Machine Learning (m/w)

Michael Page, Berlin about 1 month ago

00 61% match

#### **SCHWARZ**

#### Senior Data Scientist (w/m)

Schwarz Dienstleistung KG, Neckarsulm 3 days ago

@ 68% match



#### Big Data Software Engineer (m/w)

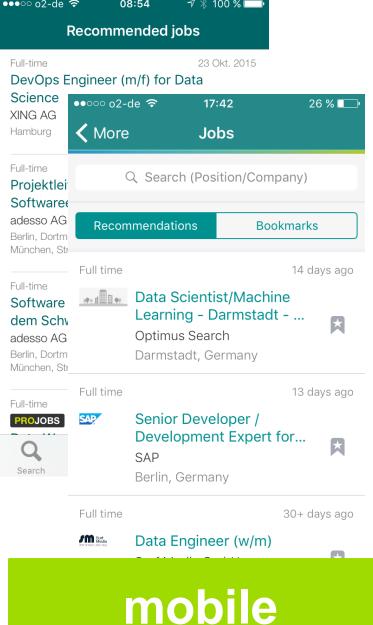
OPITZ CONSULTING Deutschland GmbH, Berli... 12 days ago

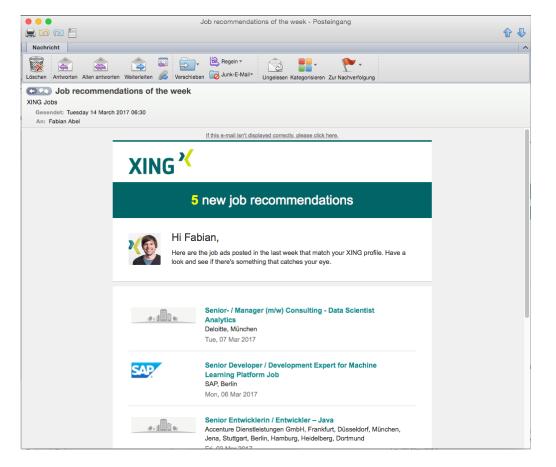
76% match

→ 13 more job recommendations









# email



# Goals / Triangle of contradiction

- relevant recos
- no spam

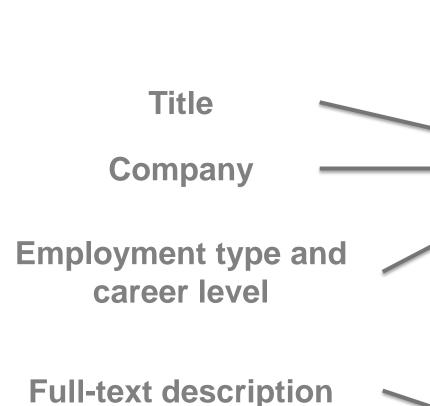


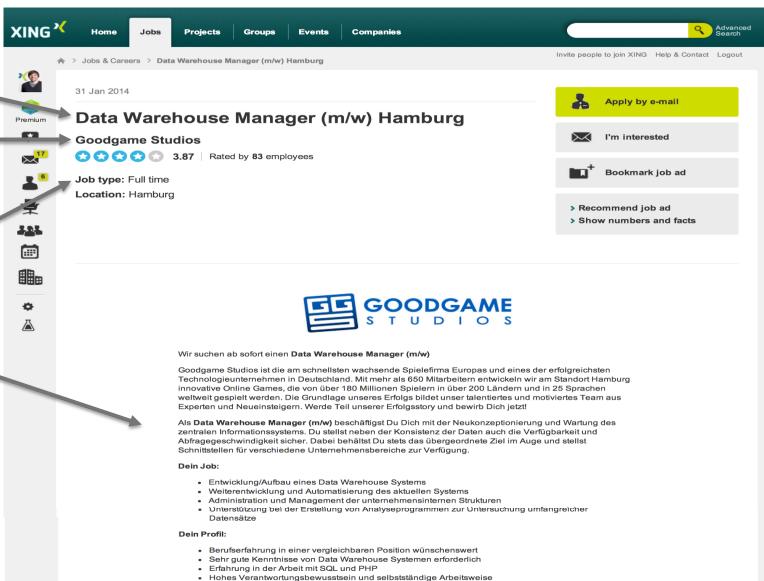
- relevant candidates
- high reach

- high revenue (e.g. many clicks on paid content)
- happy customers

# Key properties of a job posting



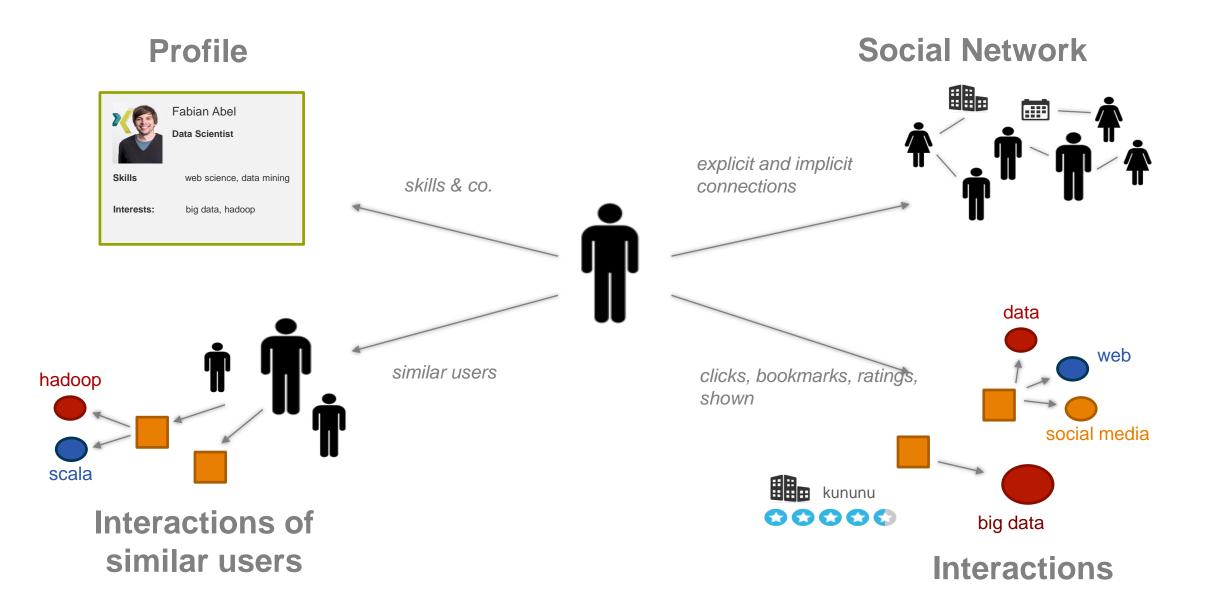




· Sehr gute Deutsch- und Englischkenntnisse in Wort und Schrift

## Key sources for understanding user demands







# Recommender strategies

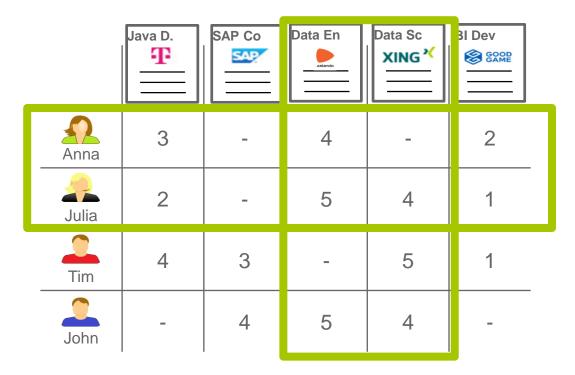
- Content-based filtering
  - explicit user profile
  - implicitly given interest profile / inferred attributes
- Item-to-item recommendations (more like this)
- (Pseudo) collaborative filtering



## **Collaborative filtering**

#### Theory: User-based and Item-based CF

#### **User-Item-Rating Matrix**



#### **User-based CF:**

- Compare users based on their ratings (e.g. cosine sim.)
- Use the n most similar users to predict a rating on an item

#### Item-based CF:

- Compare items based on their ratings (e.g. cosine sim.)
- Use the n most similar items to predict a rating from a user (simple weight average)



## **Collaborative filtering**

Reality: Ultra sparse User-Item Matrix and primarily implicit feedback

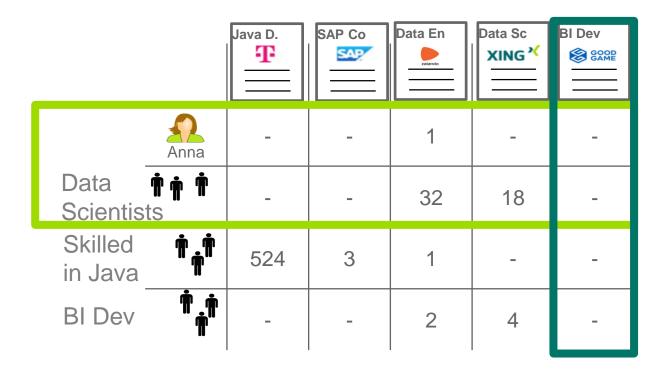
	Java D.  T	SAP Co	Data En	Data Sc XING X	BI Dev
Anna	-	-	1	-	-
Julia	-	-	-	-	-
Tim	-	-	-	-	-
John	1	-	-	-	-

High level of sparsity: classical collaborative fitering (incl. matrix factorization) does not work



## **Collaborative filtering**

Reality: Ultra sparse User-Item Matrix and primarily implicit feedback



#### Pseudo CF:

- Cluster users based on...
  - jobrole
  - skills
  - field of study
- Recommend items that similar users (= clusters) interacted with

New item problem remains...



# Content-based filtering

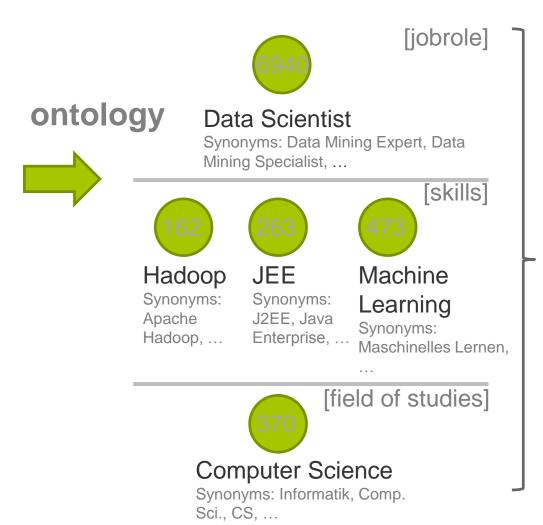
Example: semantic search

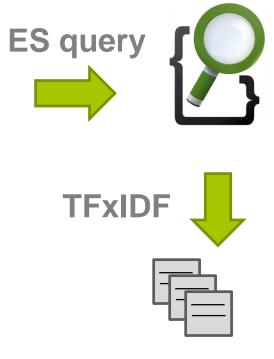


Skills: ML, j2ee

**Interests:** Hadoop

**Education:** Informatik







## Content-based filtering

Example: More-like-this component

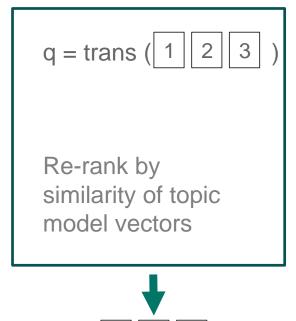
# Bookmarked, rated and applied-to job postings



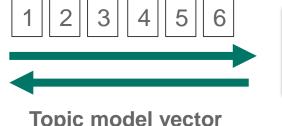




# Recommending similar items







(Doc2Vec vs. LSTM)

Topic model vector representations





# Filtering and Re-ranking

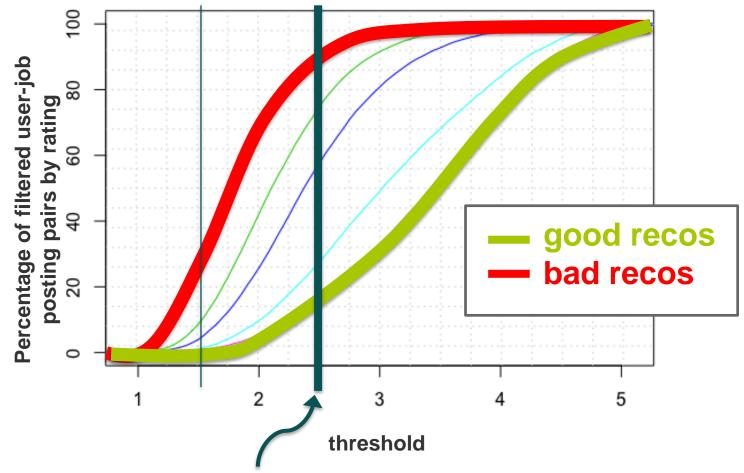
- career level filtering
- less-like-this
- same company filtering
- boosting jobs from cities where people have contacts
- boosting paid content
- outlier filtering
- **.**...



# Outlier Filtering: Trade-off between killing bad recommendations and keeping good ones

#### Approach:

- 1. Predict a rating for each user and its top-x recommendations
- 2. Remove recos with a rating below the threshold

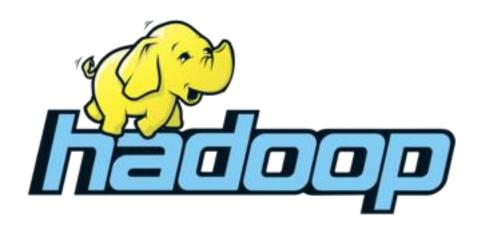


Example: with a threshold of 2.5 we kill 86% of the bad and 18% of the good recos



# Bulding Recommender Systems









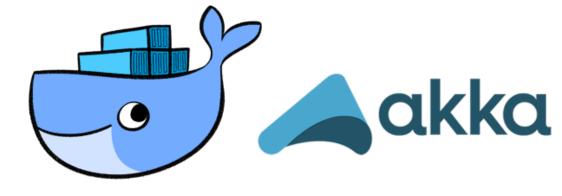


# Scala



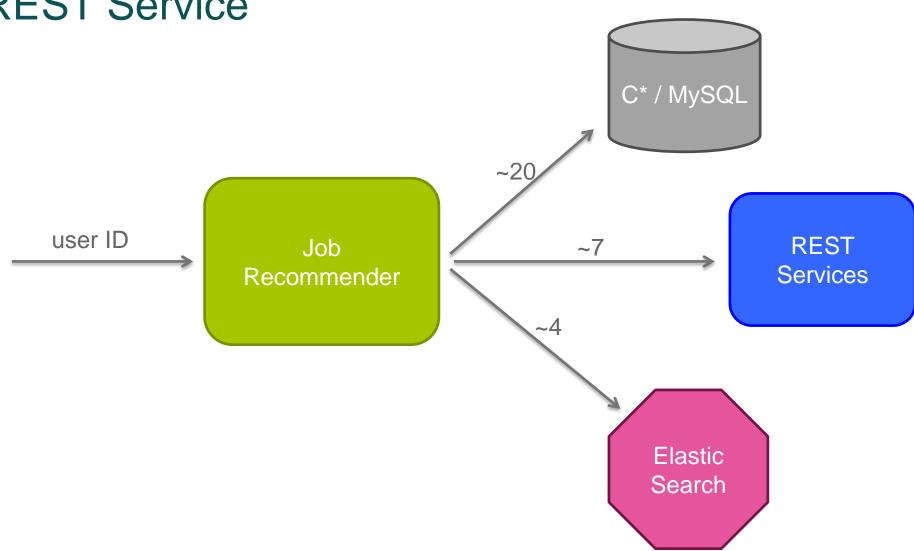








## **REST Service**

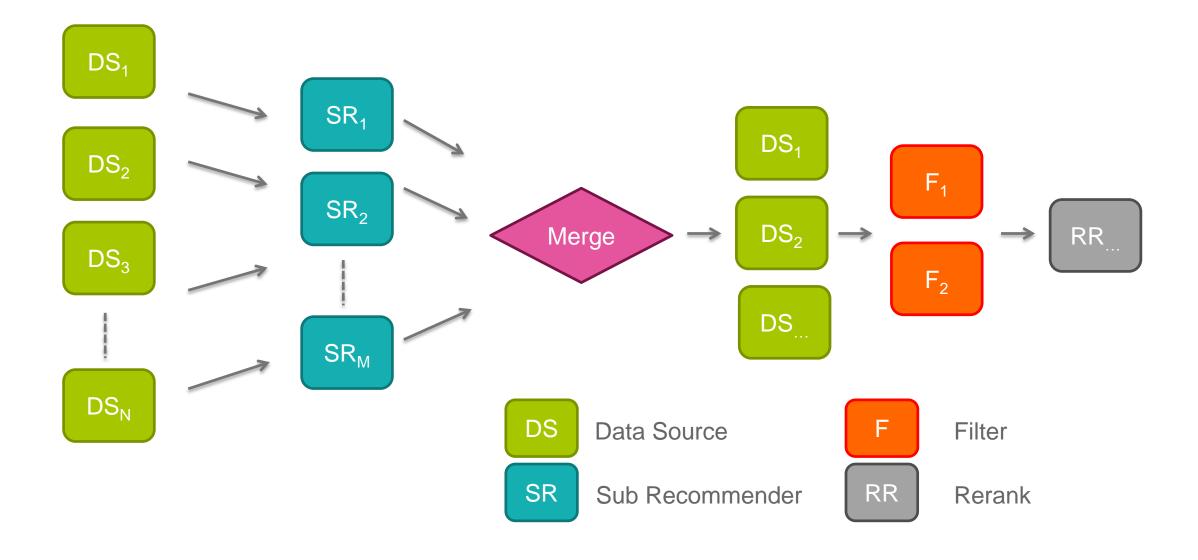








#### Internal recommender structure





# Mixture of Online & Batch Processing

#### **Online data**

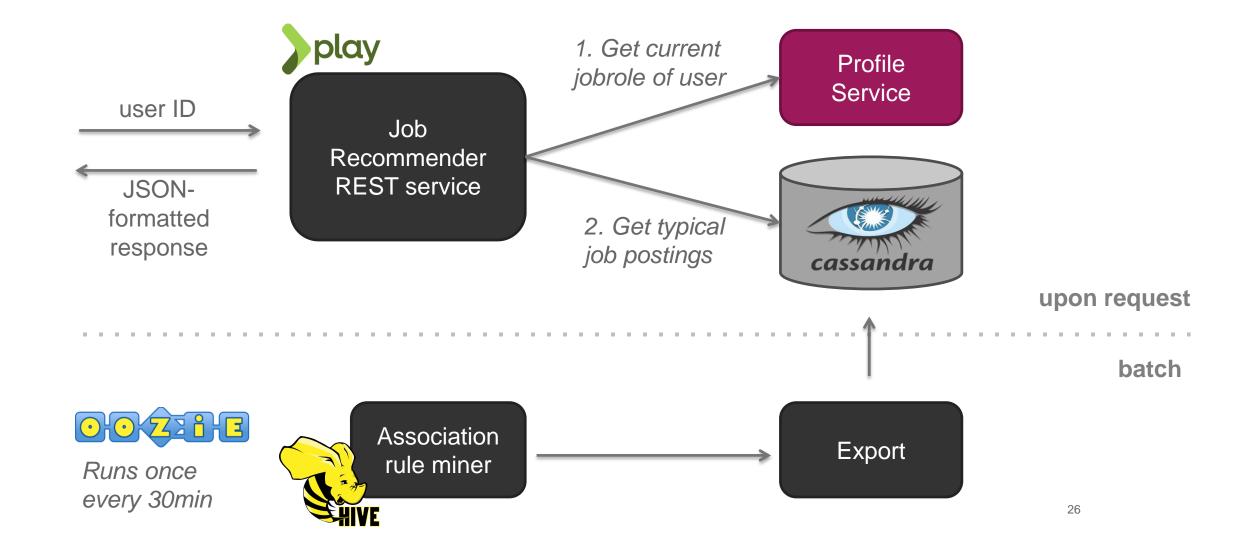
- Lookup or computation takes milliseconds
- Often required when data must be up-to-date (e.g. contextual user info)
- Examples:
  - User profile data
  - Contacts of the user
  - Negative feedback (e.g. ratings)

#### Pre-computed data (batch)

- Takes minutes or hours to compute
- Often required when a "complete picture" (also about other users) is necessary
- Examples:
  - Interaction-based profiles
  - Association rules
  - Topic modeling (Doc2Vec, LSTM)



## Example: Users in jobrole X typically click on





# Deployment of RecSys Models



# Examples of models used in production

Use Case	Type of model		
Categorizing job posting	Logistic regression (>100k features)		
Enrichment of job postings	Hierarchical Clustering (hierarchical K-Means)		
Identifying similar job postings	Doc2Vec-based topic modeling; LSTM		
Pseudo-CF	Association rule mining		
Outlier filtering	XGBoost (~100 features, optimizing RMSE)		
Core Ranking of job recos	XGBoost (~140 features, optimizing pairwise loss)		
Estimating willingness to change jobs	XGBoost (~90 features, optimizing cross entropy)		
Estimating user preferences	Naïve Bayes		

# Degree of automation in ML

**)**(

high

Degree of automation

Models and features are automatically constructed, refined, optimized

Models and features are automatically (re-)learned, refined, optimized

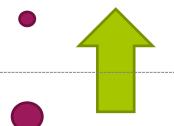
Model-based algorithms are frequently relearned (semi-automated, re-prod.),

Model-based algorithms are manually learned once (not reproducable)

Algorithms based on data analysis

Hacking: hand-crafted algorithms





ML with human supervision



Involvment of

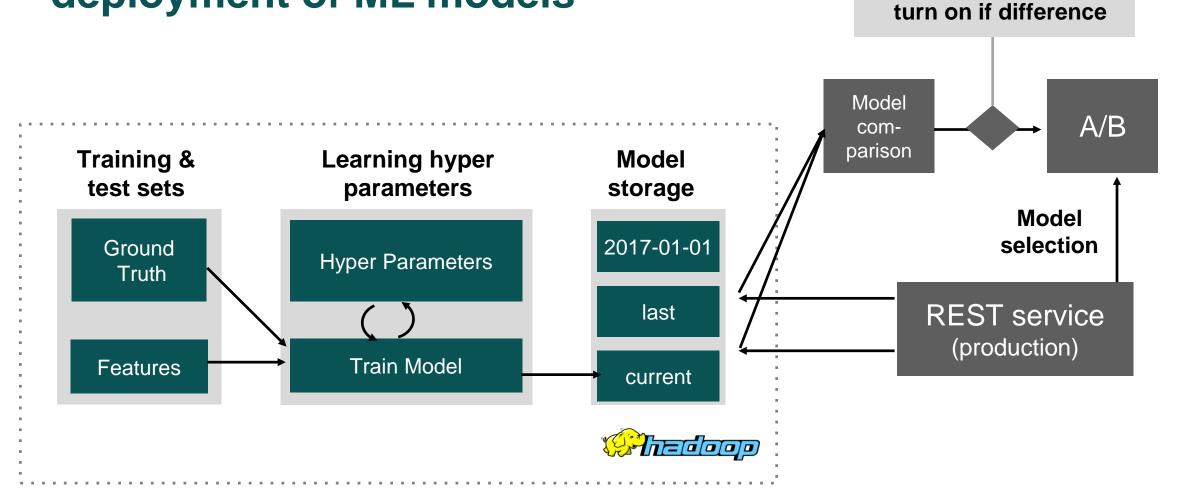
humans



low



# Automated learning & deployment of ML models



# Thank you

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http://bit.ly/data-science-team



