Balázs Bárány

Data Scientist

pgconf.de 2015

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Data Science with PostgreSQL Business & data understanding Preprocessing Modeling Evaluation Deployment

Summary



Data Science with PostgreSQL LIntroduction – What is Data Science?

#### Sexiest job of the 21st century

According to Google, LinkedIn, ...



Data Science with PostgreSQL LIntroduction – What is Data Science?

#### Sexiest job of the 21st century

According to Google, LinkedIn, ...

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▶ Who is a Data Scientist?

Data Science with PostgreSQL Introduction – What is Data Science?

#### Data Science Venn Diagram



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Data Science with PostgreSQL Introduction - What is Data Science?

#### Tasks of data scientists

Get data from various sources

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► Big data?

Data Science with PostgreSQL LIntroduction - What is Data Science?

#### Tasks of data scientists

- Get data from various sources
  - ► Big data?
- Mash up & format for analysis



Data Science with PostgreSQL LIntroduction - What is Data Science?

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► Analyze & visualize

Data Science with PostgreSQL —Introduction – What is Data Science?

#### Tasks of data scientists

- Get data from various sources
  - Big data?
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- Analyze & visualize
- ► Predict & prescribe

Data Science with PostgreSQL —Introduction – What is Data Science?

#### Tasks of data scientists

- Get data from various sources
  - Big data?
- Mash up & format for analysis

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- Analyze & visualize
- Predict & prescribe
- Operationalize

Introduction – What is Data Science?

Process model

#### The Data Mining process



Cross Industry Standard Process for Data Mining (Kenneth Jensen/Wikimedia Commons)

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#### Tools and methods

## Tools and methods



### Scripting and programming

#### ► R

- Python with extensions
- Octave/Matlab, other mathematic languages
- Hadoop and Big Data programming libraries (mostly Java)

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Cloud services

#### Integrated GUI tools

- ► (partly) Open Source: RapidMiner, KNIME, Orange
- Data Warehouse tools extended for analytics: Pentaho, Talend

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- ► Many commercial tools, e. g. SAS, IBM SPSS
- ► Hadoop-related newcomers: e. g. Datameer

#### Data Infrastructure

- Databases and data stores
  - Relational, NoSQL
  - Hadoop clusters
  - In-memory
- Data streams
- ► Free-form data: text, images, video, audio, ...

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- Web APIs
- Open Data

#### Data acquisition and preprocessing

Data ingestion in raw format



#### Data acquisition and preprocessing

- Data ingestion in raw format
- ► Joining, aggregating, filtering, calculating, ...



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- Data cleansing
  - Missing values
  - Abnormal values

#### Data acquisition and preprocessing

- Data ingestion in raw format
- ► Joining, aggregating, filtering, calculating, ...

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- Data cleansing
  - Missing values
  - Abnormal values
- Result: data set suitable for analytics

#### **Predictive Modeling**

- Supervised and unsupervised methods
  - Target variable known or not



### **Predictive Modeling**

- Supervised and unsupervised methods
  - Target variable known or not
- ► Classification (supervised): Prediction of a class or category

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Regression (supervised): Prediction of numeric value

### **Predictive Modeling**

- Supervised and unsupervised methods
  - Target variable known or not
- ► Classification (supervised): Prediction of a class or category
- Regression (supervised): Prediction of numeric value
- Clustering (unsupervised): Automatic "grouping" of data
- Association analysis, outlier detection, time series prediction,
  ...

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#### Deployment and operationalization

- ► Model application to new data => prediction + confidence
- What to do with predictions?



#### Deployment and operationalization

► Model application to new data => prediction + confidence

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- What to do with predictions?
- Store in ERP or CRM
- ► Tell someone (email, popup)
- Add a label (e. g. mark email as spam)

...

### Deployment and operationalization

▶ Model application to new data => prediction + confidence

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- What to do with predictions?
- Store in ERP or CRM
- Tell someone (email, popup)
- Add a label (e. g. mark email as spam)
- Interrupt financial transaction => prescription
- Order supplies => prescription

### Data Science with PostgreSQL

# Doing Data Science with PostgreSQL



#### Caveats

► This stuff is not easy



#### Caveats

- This stuff is not easy
- Must be root and postgres
  - Maintain your PostgreSQL yourself
  - Able to compile stuff



#### Caveats

- This stuff is not easy
- Must be root and postgres
  - Maintain your PostgreSQL yourself

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- Able to compile stuff
- You should ask ;-)
  - your boss
  - co-workers
  - customer

### Data Science with PostgreSQL

## Business & data understanding



#### Business understanding

- What is the purpose of the business?
- What are existing processes?
- Drivers of business success



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- What are existing processes?
- Drivers of business success
- Project goals and challenges
- Availability of data and resources
- Success criteria



Business understanding

- What is the purpose of the business?
- What are existing processes?
- Drivers of business success
- Project goals and challenges
- Availability of data and resources
- Success criteria
- Not a technical activity, PostgreSQL can't help much

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### Data understanding

#### Existing data

- Entities and covered concepts
- Complete? Correct? In suitable form?
- ► Usable? (regulations, access constraints, ...)



### Data understanding

- Existing data
  - Entities and covered concepts
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- Connecting separate data sources
  - Simple or complex IDs

### Data understanding

- Existing data
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- Connecting separate data sources
  - Simple or complex IDs
- Data size
  - Too small
  - Too big
### Data understanding

### Existing data

- Entities and covered concepts
- ► Complete? Correct? In suitable form?
- ► Usable? (regulations, access constraints, ...)

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- Connecting separate data sources
  - Simple or complex IDs
- Data size
  - Too small
  - Too big
- Suitability for predictive modeling
  - Target variable?
  - Attribute types

### Data understanding with PostgreSQL

- ► Get data into PostgreSQL
  - Classical import process
  - Foreign Data Wrappers



### Data understanding with PostgreSQL

- ► Get data into PostgreSQL
  - Classical import process
  - Foreign Data Wrappers
- Analyze data distribution
  - Group by and aggregate
    - ► Count, Count Distinct, Min, Max
  - Count NULLs
  - Search for missing links (incomplete foreign keys)

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- ► Analyze "surprizes"
  - Impossible values
  - Missing values in "required" fields

### Data understanding with PostgreSQL - summary

- Good SQL knowledge required
- Tedious manual process
  - repetitive
  - not suitable for large number of attributes

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No built-in visualization

### Data understanding with PostgreSQL - summary

- Good SQL knowledge required
- Tedious manual process
  - repetitive
  - not suitable for large number of attributes

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- No built-in visualization
- Or maybe...

Data Science with PostgreSQL

Business & data understanding

### SQL barchart output

foreign_table_options	5	###
foreign tables		###
information_schema_catalog_name		Menü Tooltip Wab Baarbakan Expaniaren
key column usage		#####
parameters	32	#######################################
pg foreign data wrappers		####
pg foreign servers		#####
pg foreign table columns		##
pg foreign tables		####
pg user mappings		####
referential constraints		#####
role column grants		####
role routine grants		######
role table grants		####
role udt grants		####
role_usage_grants		####
routine_privileges		######
routines	82	*******
schemata		####
sequences	12	#######
sql_features		####
sql_implementation_info		###
sql languages		####
sql packages		###
sql_parts		###
sql_sizing		##
sql_sizing_profiles		###

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Data Science with PostgreSQL

└─ Business & data understanding

### Bar chart from GUI tool



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- LData Science with PostgreSQL
  - └─ Business & data understanding

### Boxplot output



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### Data understanding wrap up

- DBMS not built for this
- It can support more specialized tools

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### Data understanding wrap up

- DBMS not built for this
- It can support more specialized tools
- Introduction: R
  - "A free software environment for statistical computing and graphics"

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Available in PostgreSQL

### PL/R: A statistical language for PostgreSQL

- R as a standalone language
  - Mathematical and statistical methods
  - Powerful visualization functions
  - Classical, modern and bleeding edge modeling
  - Arrays and data frames are central data types

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Operates only in memory

### PL/R: A statistical language for PostgreSQL

- R as a standalone language
  - Mathematical and statistical methods
  - Powerful visualization functions
  - Classical, modern and bleeding edge modeling
  - Arrays and data frames are central data types
  - Operates only in memory
- ► PL/R: R as a loadable procedural language for PostgreSQL

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- ► First released in 2003 by Joe Conway
- License: GPL

### R usage outside of PostgreSQL

- Development environments
  - ► RStudio (AGPL or commercial, local & web)
  - RKWard, Cantor (KDE projects)
  - StatET (Eclipse)
- ► Frontends
  - R Commander
  - Deducer
  - Rattle
- Web framework: Shiny (AGPL or commercial)

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### Working with R in PostgreSQL

Install functions in the database

```
Example
select install_rcmd('
    myfunction <-function(x)
      {print(x)}
');</pre>
```

Install without function body

### Example

```
CREATE FUNCTION rnorm
  (n integer, mean double precision, sd double precision)
RETURNS double precision[]
AS "
LANGUAGE 'plr';
```

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### Using R in PostgreSQL for data understanding

- Advanced visualization
- Data distributions
- Advanced statistics



### Using R in PostgreSQL for data understanding

- Advanced visualization
- Data distributions
- Advanced statistics
- Execution in the database
  - Clumsy, but direct data access

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### Using R in PostgreSQL for data understanding

- Advanced visualization
- Data distributions
- Advanced statistics
- Execution in the database
  - Clumsy, but direct data access
- Execution outside
  - Simple and interactive, but data transfer

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### Data Science with PostgreSQL

## Preprocessing



### Preprocessing

What databases are built for



### Preprocessing

- What databases are built for
- Rows: very dynamic
  - Easy to create new rows by joining

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- Easy to filter
- Columns: not so much
  - Easy to create new columns
  - Only explicit access

### Preprocessing

- What databases are built for
- Rows: very dynamic
  - Easy to create new rows by joining
  - Easy to filter
- Columns: not so much
  - Easy to create new columns
  - Only explicit access
- Wider interpretation of preprocessing
  - Enrichment with external data
  - New attributes from existing ones

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- Recoding, recalculation
- Missing value handling

Preprocessing

### Preprocessing: organizing workflow

- Common Table Expressions
  - organize processing steps
  - partial and intermediate results

### Example

```
WITH source AS (
   SELECT *, ROW_NUMBER() OVER () AS rownum
   FROM source_table
),
no_missings AS (
   SELECT *
   FROM source
   WHERE field1 IS NOT NULL
   AND field2 IS NOT NULL
)
etc.
```

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Data Science with PostgreSQL

Preprocessing

### Preprocessing: attribute creation

Aggregation



### Preprocessing: attribute creation

- Aggregation
- Partial aggregation by window functions
  - In-group measures, e. g. ratio
  - ▶ att / SUM(att) OVER (PARTITION BY ...)



### Preprocessing: attribute creation

- Aggregation
- Partial aggregation by window functions
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  - ▶ att / SUM(att) OVER (PARTITION BY ...)
  - In-group numbering
  - ► ROW\_NUMBER() OVER (PARTITION BY ... ORDER BY ...)

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Preprocessing

### Preprocessing: attribute creation

- Aggregation
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- Comparing to previous/next value
  - ▶ att LAG(att, 1) OVER (ORDER BY ...)

Preprocessing

### Preprocessing: attribute creation

- Aggregation
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- Comparing to previous/next value
  - ▶ att LAG(att, 1) OVER (ORDER BY ...)
- Much easier in SQL than programming languages and data mining tools

### Preprocessing: enrichment

PostGIS for geodata



### Preprocessing: enrichment

- PostGIS for geodata
- Foreign data wrappers (see PostgreSQL Wiki)



### Preprocessing: enrichment

- PostGIS for geodata
- Foreign data wrappers (see PostgreSQL Wiki)
  - Other databases (other PostgreSQL server, MySQL, Oracle, MSSQL, JDBC, SQL Alchemy ...)
  - ► NoSQL databases (MongoDB, Cassandra, CouchDB, Redis, ...)

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Big Data (Hadoop Hive, Impala)

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- Big Data (Hadoop Hive, Impala)
- Network sources Multicorn (RSS, IMAP, Twitter, S3, ...)
- Files (CSV, ZIP, JSON, ...)

### Preprocessing: enrichment

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- Big Data (Hadoop Hive, Impala)
- Network sources Multicorn (RSS, IMAP, Twitter, S3, ...)
- Files (CSV, ZIP, JSON, ...)
- Write your own in C or Python or Ruby

### Data Science with PostgreSQL

# Modeling



### Model development

Machine learning algorithms not well suited for SQL


#### Model development

Machine learning algorithms not well suited for SQL

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- Some attempts to build them
  - Naive Bayes, Linear Regression
  - Difficult for more advanced algorithms

#### Model development

Machine learning algorithms not well suited for SQL

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- Some attempts to build them
  - Naive Bayes, Linear Regression
  - Difficult for more advanced algorithms
- Better done in specialized language or tool
  - ► PL/R
  - PL/Python





- Python procedural language available in PostgreSQL
- scikit-learn: Machine learning toolbox for Python
  - Classification, regression, clustering
  - Model selection, validation
  - Preprocessing
- matplotlib: Generic and statistical plotting library

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PL/Python is an alternative to PL/R

#### Data Science with PostgreSQL

# Evaluation



#### Evaluation of modeling results

- Models return predictions
- Prediction can be compared to known result (target variable)
- ► Measures of model performance: Accuracy, precision, recall, ...

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Results on the training set meaningless

#### Evaluation of modeling results

- Models return predictions
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- Results on the training set meaningless
- Split validation
- Cross validation

#### **Evaluation results**

- "Good result" depends on the application
- If not good enough,



#### **Evaluation results**

"Good result" depends on the application

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- If not good enough,
  - ► get more data

#### **Evaluation results**

- "Good result" depends on the application
- If not good enough,
  - get more data
  - do more preprocessing



#### **Evaluation results**

"Good result" depends on the application

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- If not good enough,
  - get more data
  - do more preprocessing
  - select better classifier

#### **Evaluation results**

- "Good result" depends on the application
- If not good enough,
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  - select better classifier
  - optimize classifier parameters

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#### **Evaluation results**

- "Good result" depends on the application
- If not good enough,
  - ► get more data
  - do more preprocessing
  - select better classifier
  - optimize classifier parameters
- Cycle: preprocessing modeling evaluation

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Better done in data mining environment

Data Science with PostgreSQL

Deployment

#### Data Science with PostgreSQL

# Deployment





Advantages of deployment in the database:

Less overhead





Advantages of deployment in the database:

- Less overhead
- Instant application using triggers





Advantages of deployment in the database:

- Less overhead
- Instant application using triggers
- Well-known execution environment

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Advantages of deployment in the database:

- Less overhead
- Instant application using triggers
- Well-known execution environment
- Functionality available over standard interface

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Advantages of deployment in the database:

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- Functionality available over standard interface

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Some models easily expressed in SQL

#### Deployment of PL/R or PL/Python models

Model developed in database or outside



# Deployment of PL/R or PL/Python models

- Model developed in database or outside
- Put into global context
  - PL/R: load("saved object", .GlobalEnv)

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- ► PL/Python: Global dictionary "GD"
- Application function in matching language
  - Uses existing model
  - Returns target variable

# Deployment of PL/R or PL/Python models

- Model developed in database or outside
- Put into global context
  - PL/R: load("saved object", .GlobalEnv)
  - ► PL/Python: Global dictionary "GD"
- Application function in matching language
  - Uses existing model
  - Returns target variable
- Trigger func or UPDATE uses application function

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PostgreSQL's support for data science tasks

Best: preprocessing, deployment





PostgreSQL's support for data science tasks

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- Best: preprocessing, deployment
- Modern SQL for preprocessing

# Summary

- PostgreSQL's support for data science tasks
  - Best: preprocessing, deployment
- Modern SQL for preprocessing
- Foreign Data Wrappers for data integration

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# Summary

- PostgreSQL's support for data science tasks
  - Best: preprocessing, deployment
- Modern SQL for preprocessing
- Foreign Data Wrappers for data integration

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Procedural languages for data mining



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- https://datascientist.at/

