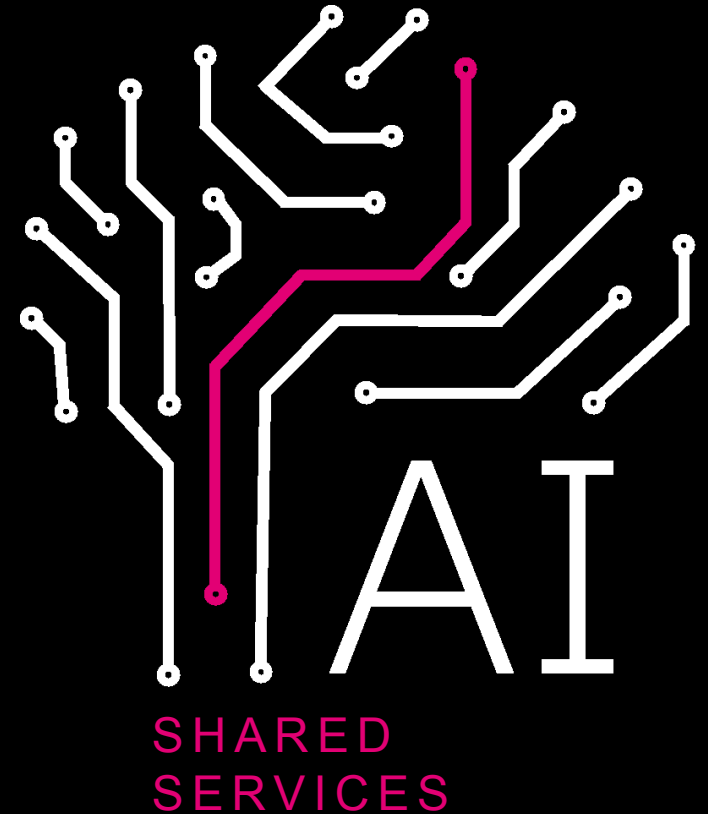


# Machine Learning in Deutsche Telekom



Who we are...



Deutsche  
Telekom  
Services  
Europe



Deutsche  
Telekom,  
T-Mobile  
CZ



LIFE IS FOR SHARING.



# DTSE in Europe

GERMANY

**Cologne**  
1007

**Darmstadt**  
388

**Hamburg**  
146

**Leipzig**  
361

**Nuremberg**  
130

SLOVAKIA

**Bratislava**  
617

**Kosice**  
237

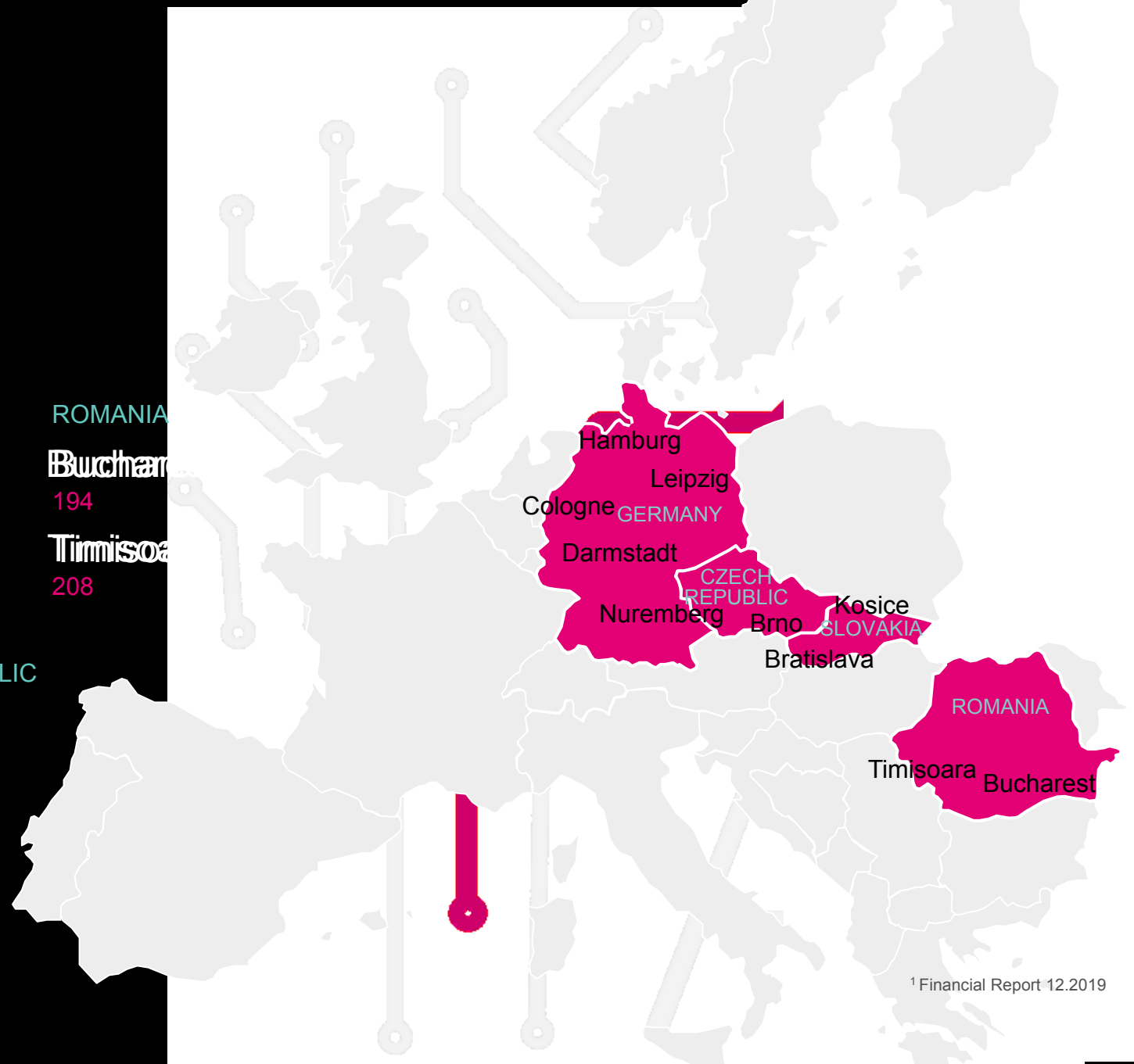
CZECH REPUBLIC

**Brno**  
133

ROMANIA

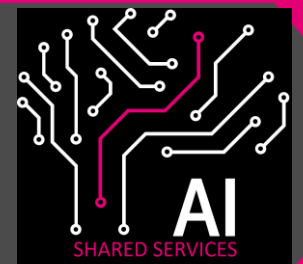
**Bucharest**  
194

**Timisoara**  
208



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<sup>1</sup> Financial Report 12.2019



# AI Shared Services: your partner for the leading digital telco

We embrace AI and agile working to enable data-driven decision making

## Our recipe for great AI projects

AGILE WORKING &  
RAPID  
DEPLOYMENT

EUROPEAN  
CROSS-  
FUNCTIONAL  
TEAMS

SMALL INVESTMENT &  
END-TO-END SERVICE

BEST TECHNOLOGY &  
CONTINUOUS  
IMPROVEMENT

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> 40

INTERNATIONAL  
TECH TALENTS

> 120

AI  
COMMUNITY  
MEMBERS



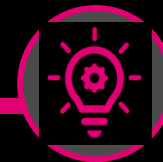
TEXT PROCESSING



PREDICTIVE  
ANALYTICS



ESG ACCELERATION



AND MUCH MORE...





**Jakub Kondek, M.Sc.**

**[j.kondek@telekom.com](mailto:j.kondek@telekom.com)**

Senior Data Scientist

Turista

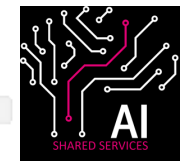
Blues enthusiast

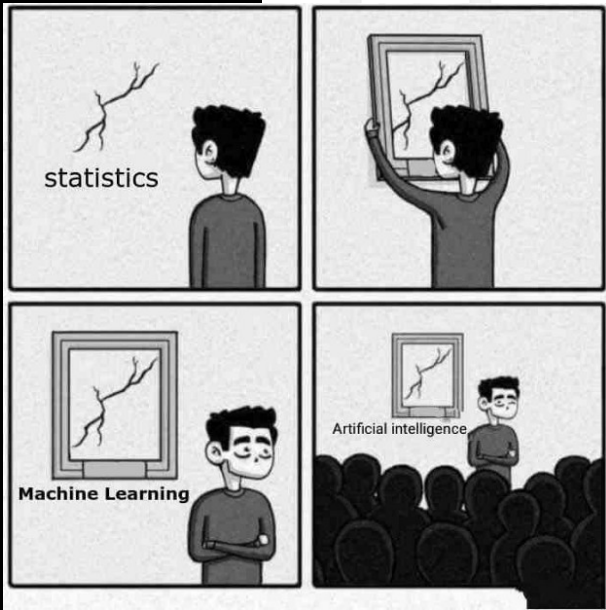


**[stepan.vondracek@telekom.com](mailto:stepan.vondracek@telekom.com)**

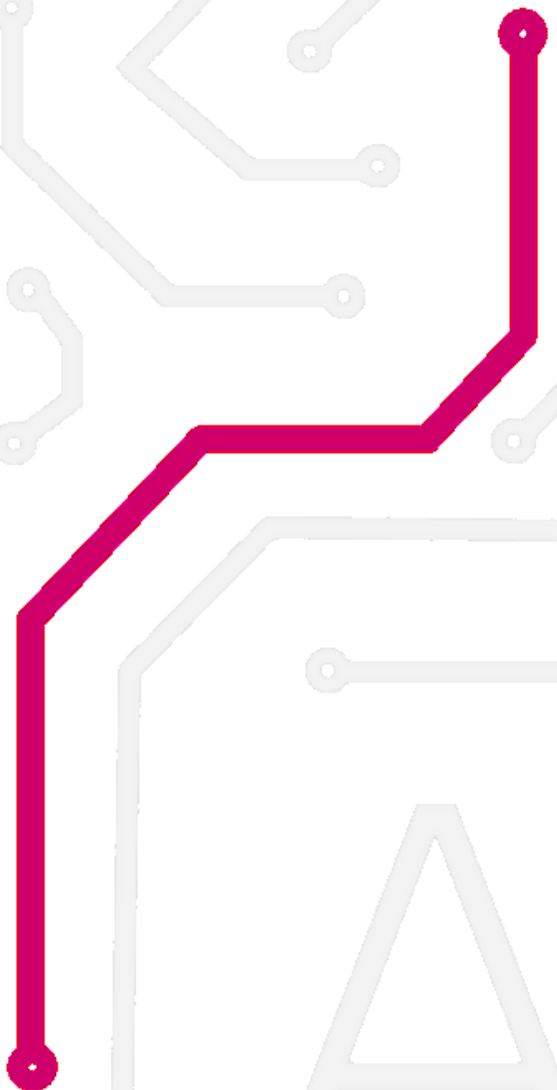


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<https://www.instagram.com/...>



# AI



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# DAILY Challenges of Data Scientist

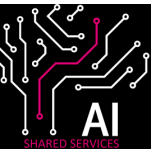
- A customers do not understand what ML does (can do)
- Communication of technological topics
- Unclear requirements ("*we would like to implement some AI...*")
- Stated problems are much simpler
- System integration
  - Is data which was used for training available for predicting
  - Do I have access/rights to data
  - Can I send prediction somewhere reasonably

\*\*\*

Possible challenge for statistics/economics graduate -> mostly IT terminology

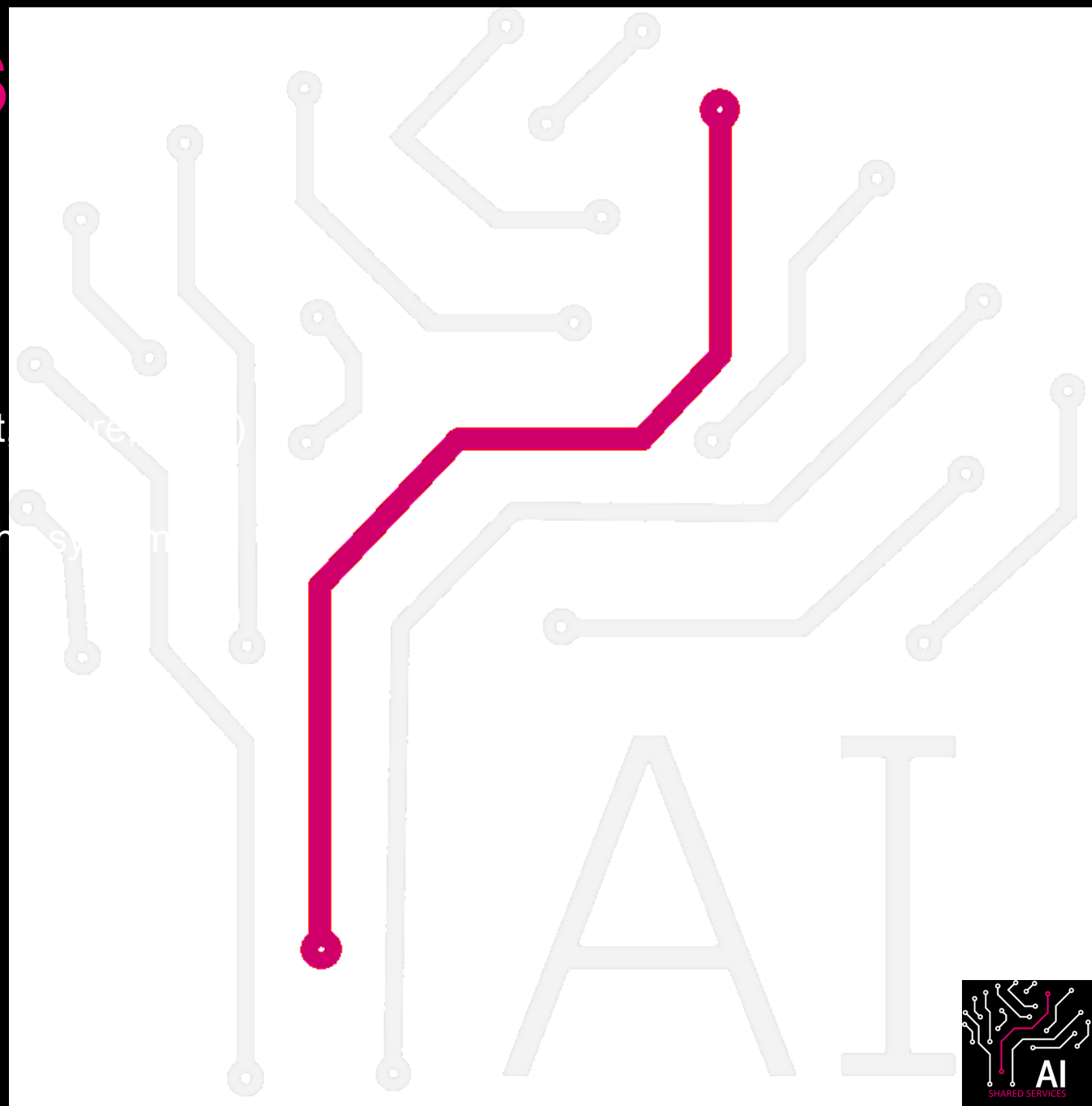


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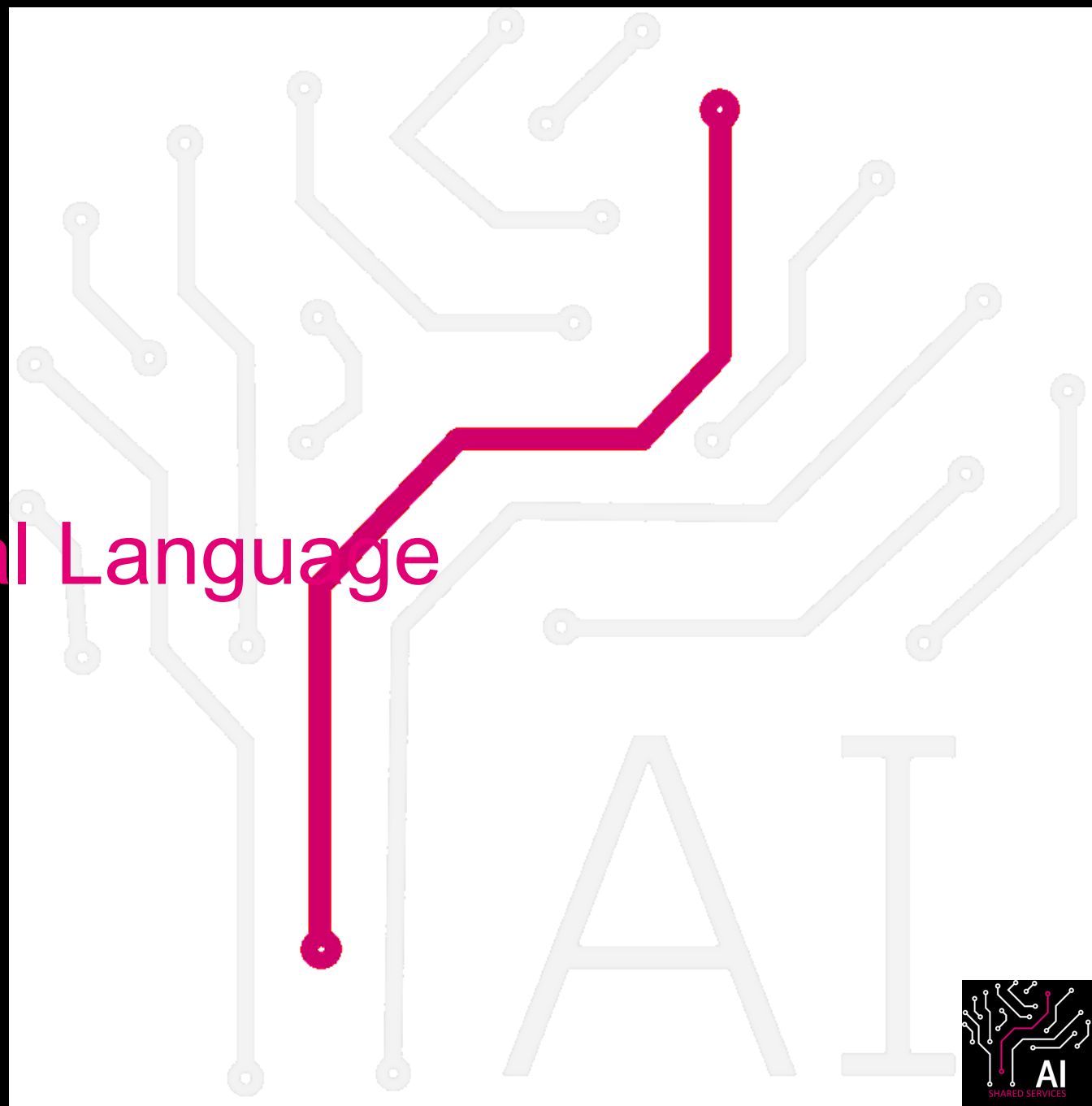
# What We Use in AIS

- Python, SQL
- Python IDEs (Pycharm, Visual Code)
- Dedicated ML server + Cloud (Openshift (referred to as ...))
- containerization (Docker, Kubernetes)
- REST API for communication between the systems
- Webservice Frameworks (fastapi)



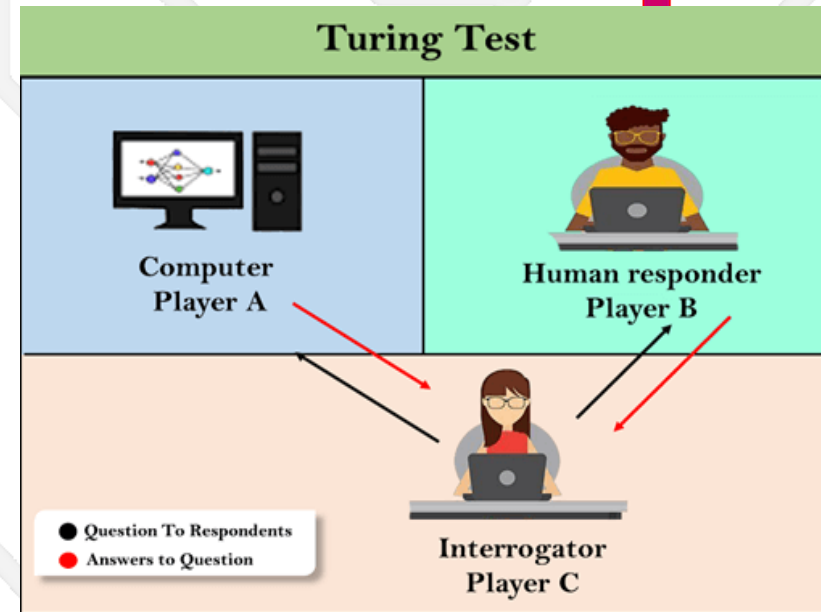


# Part I. - Natural Language Processing



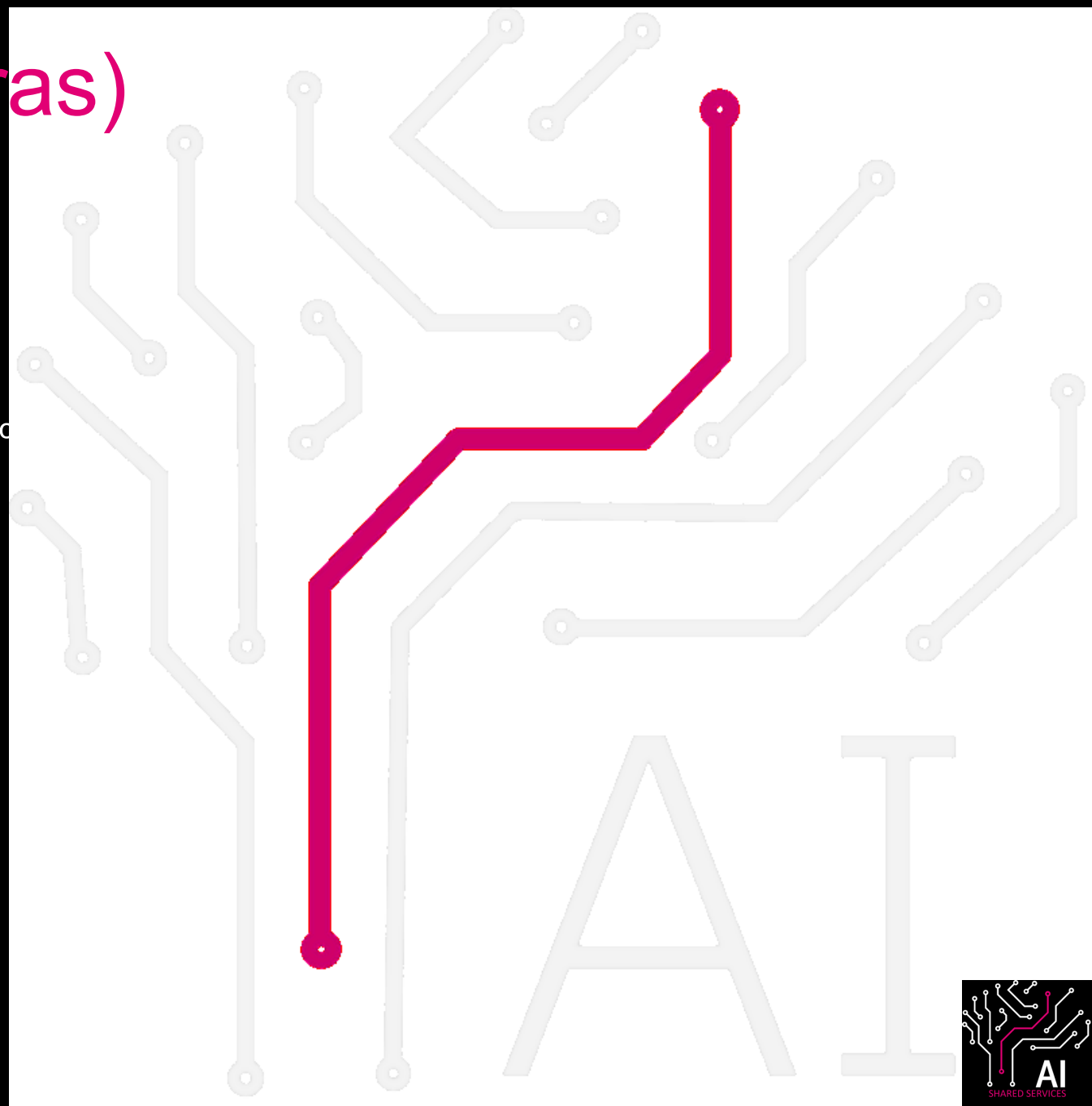
# NATURAL Language Processing (NLP)

- A field of AI dealing with interaction between computers and humans **using the natural language**
- Started in 1950s (Turing test)
- Considered to be a difficult problem in computer science
- Research in NLP is still going on
- **3 main NLP subfields:**
  - Speech Recognition
  - Natural Language Understanding
  - Natural Language Generation



# NLP Model Types (eras)

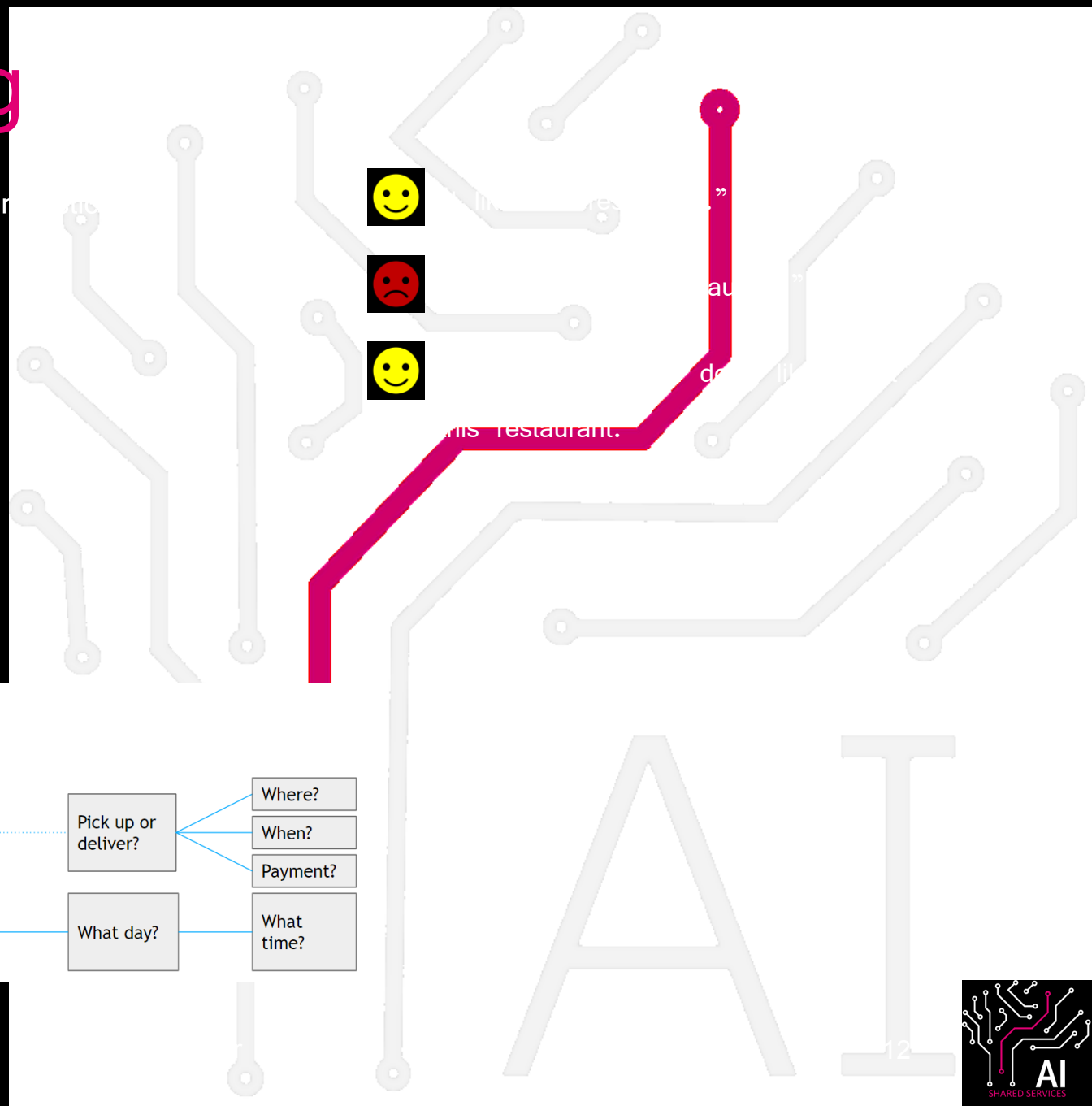
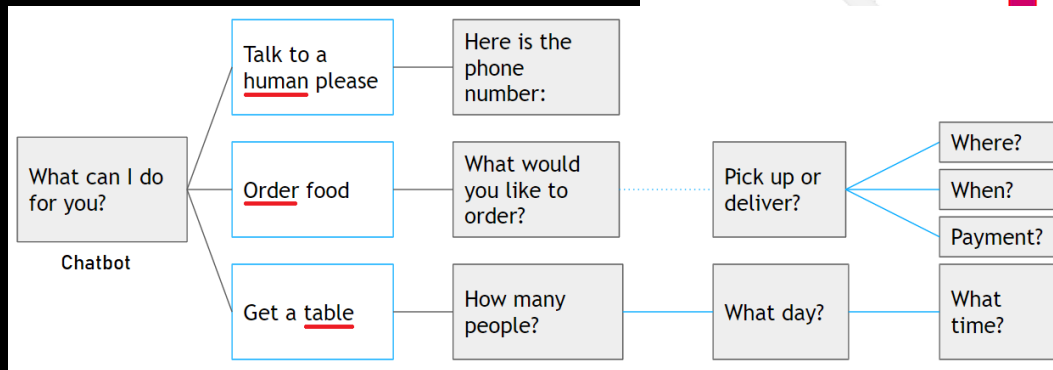
- Rule-based
- Statistical – the “traditional approach”
- Deep learning – the state of the art, “modern” approach



# Rule-Based Modeling

- A hand-crafted system of grammar rules based on linguistic rules
  - regular expressions, context-free grammars
  - often requires a skilled expert – a linguist
- Useful when we don't have enough data
- Very good interpretability
- Poor generalization and maintenance

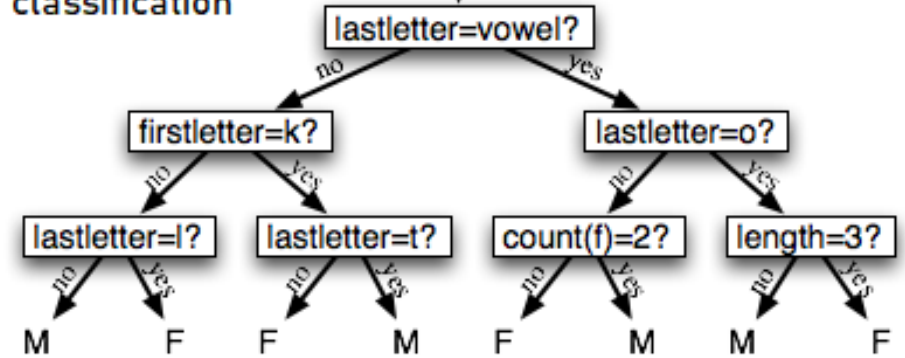
■ E.g. rule-based chatbots



# Statistical Modeling

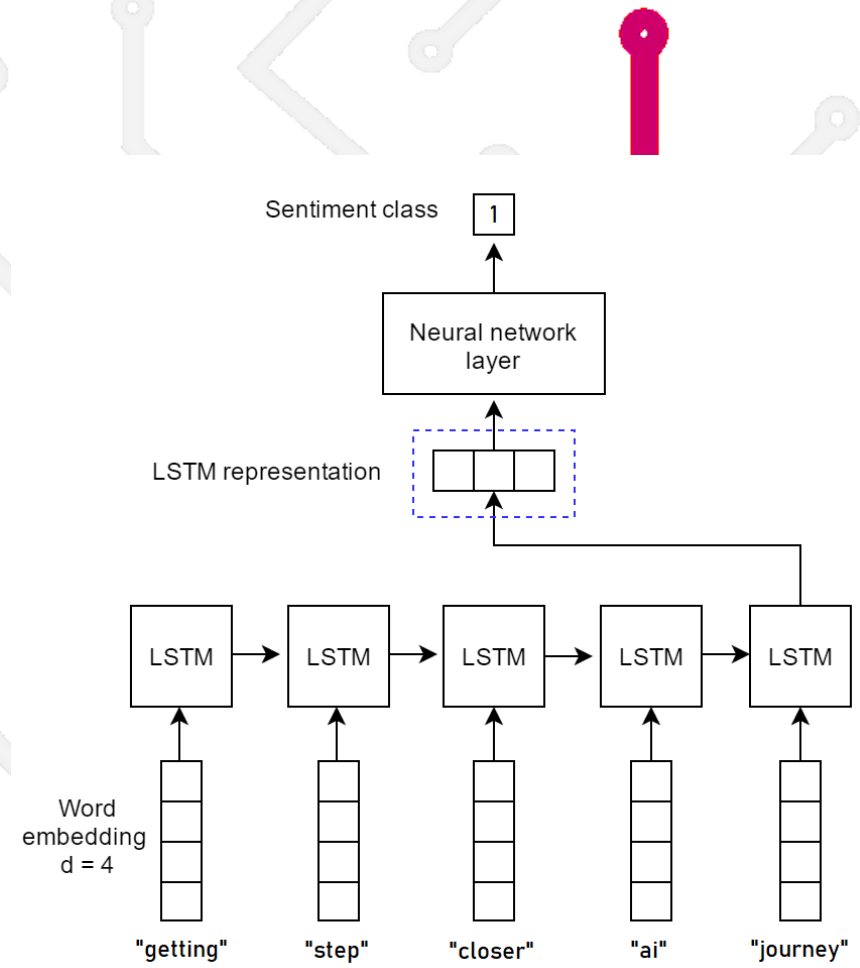
- Traditional ML models – training and testing data
- Requires moderate amount of data with annotations
- Heavy on feature engineering
  - word frequency, number of characters, edit distance capitalized, plural etc.
- Linear classifiers, Decision trees etc.
- Language Model
  - a probability distribution over sequences of words
  - can be also used for Language Generation
- N-gram Language Model
  - N-gram frequencies pre-counted on training corpus
  - $P(\text{“closer”} | \text{“getting a step”}) > P(\text{“coffee”} | \text{“getting a step”})$

Name gender classification



# Deep Learning

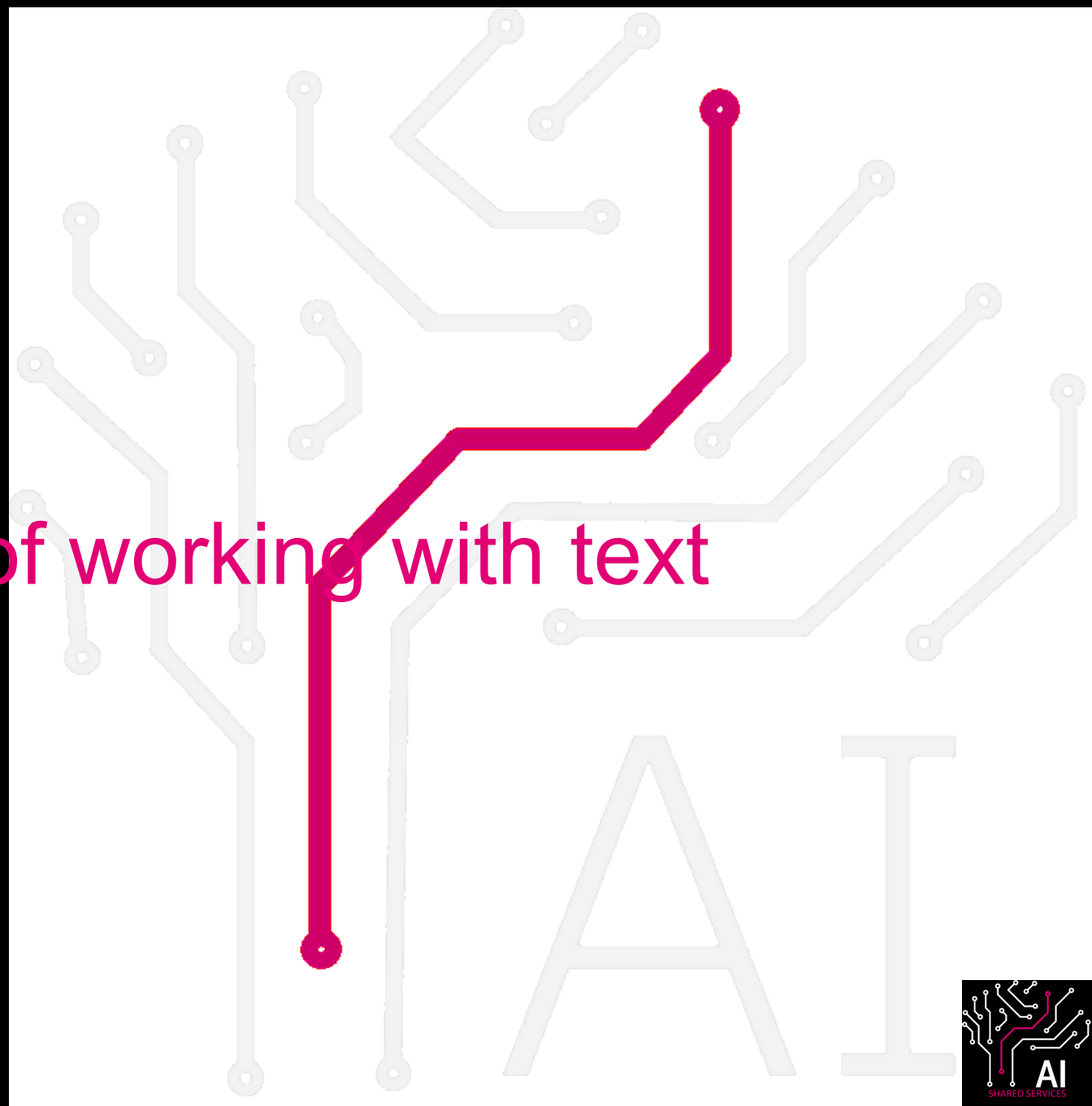
- Feature engineering is generally **skipped**
  - **raw data** as an input (word embeddings)
  - network **learns important features** itself
- Large training **corpus**
- Good **generalization**
  - **transfer learning** – reusing models trained on different tasks
- Poor **interpretability**
- **Sequence models**
  - Recurrent Neural Networks (RNN, LSTM, GRU)
  - Temporal Convolutional Networks (TCN)
- **Tasks**
  - Classification, Regression, Sequence-to-sequence



# Selected "methods" of working with text

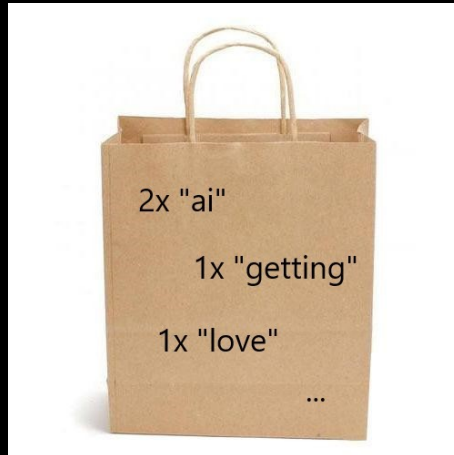


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# BAG-of-words (BOW)

- A simplifying representation, **disregards word order**
- Text is represented as a **bag (multiset) of its words**
  - **multiplicity** – number of occurrences of each word



```
from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer(tokenizer=nlk.word_tokenize, vocabulary=dictionary)

bow = vectorizer.transform([sentence])

list(zip(dictionary.keys(), bow.toarray()[0])) #word counts

[('.', 2),
 ('a', 1),
 ('ai', 2),
 ('am', 1),
 ('closer', 1),
 ('getting', 1),
 ('i', 2),
 ('journey', 1),
 ('love', 1),
 ('my', 1),
 ('on', 1),
 ('step', 1)]

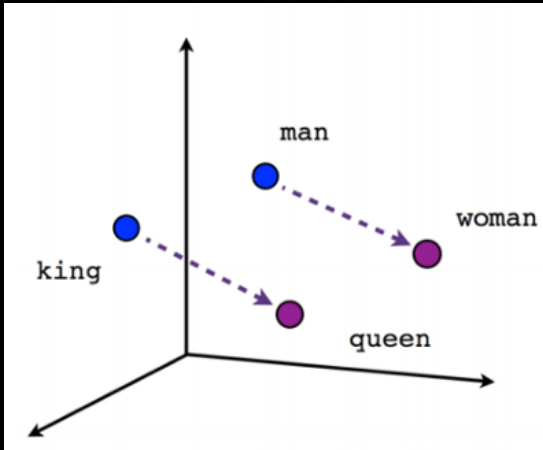
bow.toarray() #bag of words representation

array([[2, 1, 2, 1, 1, 1, 2, 1, 1, 1, 1, 1]])
```



# WORD EMBEDDINGS

- Mapping of words into vectors of real numbers
- Words are closer to each other, if they occur in similar context
- King - Man + Woman = Queen
- Most popular embedding models are Word2Vec (Tomas Mikolov), FastText, or BERT



```
import fasttext

model = fasttext.load_model("./fastText/cc.en.300.bin")

cosine_distance(model.get_word_vector("journey"), model.get_word_vector("voyage"))

0.42419618368148804

cosine_distance(model.get_word_vector("journey"), model.get_word_vector("coffee"))

0.9299457967281342
```

# LLMs @AI Shared Services – Product Athena



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# Athena Overview

- Semantic search over various data types
- Enables fast orientation in vast amount of data
- Features:
  - Language independent
  - Summarization
  - Similarity matching
  - Text generation
  - Connection to web data

**Options**

Show debug info

Which database you want to use?

riskdata1

**File Upload:**

Drag and drop files here

Limit 200MB per file - JPG, JPEG, PNG, GIF, TIFF, PDF, DOCX, XLSX, PPTX, TXT, CSV, DOC, RTF

Browse files

Answers in audio (only english)

**Athena - semantic search**

Which sports teams does Telekom sponsor? 40/100

Options

Max. number of documents from retriever 10

Answer mode Expert

Search

Telekom sponsors several sports teams, including the German record champion FC Bayern Munich, the German Football Association (DFB), Hamburger SV, Borussia Mönchengladbach, and 1. FC Köln [Document 2]. They also have partnerships with the National Men's Football Team of Germany, the 3. Liga, and the FLYERALARM Frauen-Bundesliga [Document 7]. Additionally, Telekom is involved in the eSports scene and sponsors SK Gaming [Document 8].

Specify

# Part II. - Time Series Forecasting in DTSE



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# Jak odhadnete počet lidí, kteří přijdou na naši přednášku?

- Počet lidí na semináři minulý týden
- Počet lidí ve druhém týdnu loňského
- Zohlednění počtu studentů v roční
- Geniální anotace, která určitě přiláká

# Predikce časových řad

1. PRAVIDELNĚ uspořádané hodnoty
2. Předpoklad, že (některé) aspekty z minulosti budou pokračovat v budoucnosti a ovlivní budoucnost
3. Možnost zahrnout další vysvětlující faktory

- V Deutsche Telekom hlavně měsíční

Date	Position	Value
2022-01-01 00:00:00	Revenues	104
2022-02-01 00:00:00	Revenues	101
2022-03-01 00:00:00	Revenues	103
2022-04-01 00:00:00	Revenues	108
2022-05-01 00:00:00	Revenues	112
2022-06-01 00:00:00	Revenues	115
2022-07-01 00:00:00	Revenues	129
2022-08-01 00:00:00	Revenues	134
2022-09-01 00:00:00	Revenues	127
2022-10-01 00:00:00	Revenues	116
2022-11-01 00:00:00	Revenues	111
2022-12-01 00:00:00	Revenues	?
2023-01-01 00:00:00	Revenues	?
2023-02-01 00:00:00	Revenues	?

# Proč?

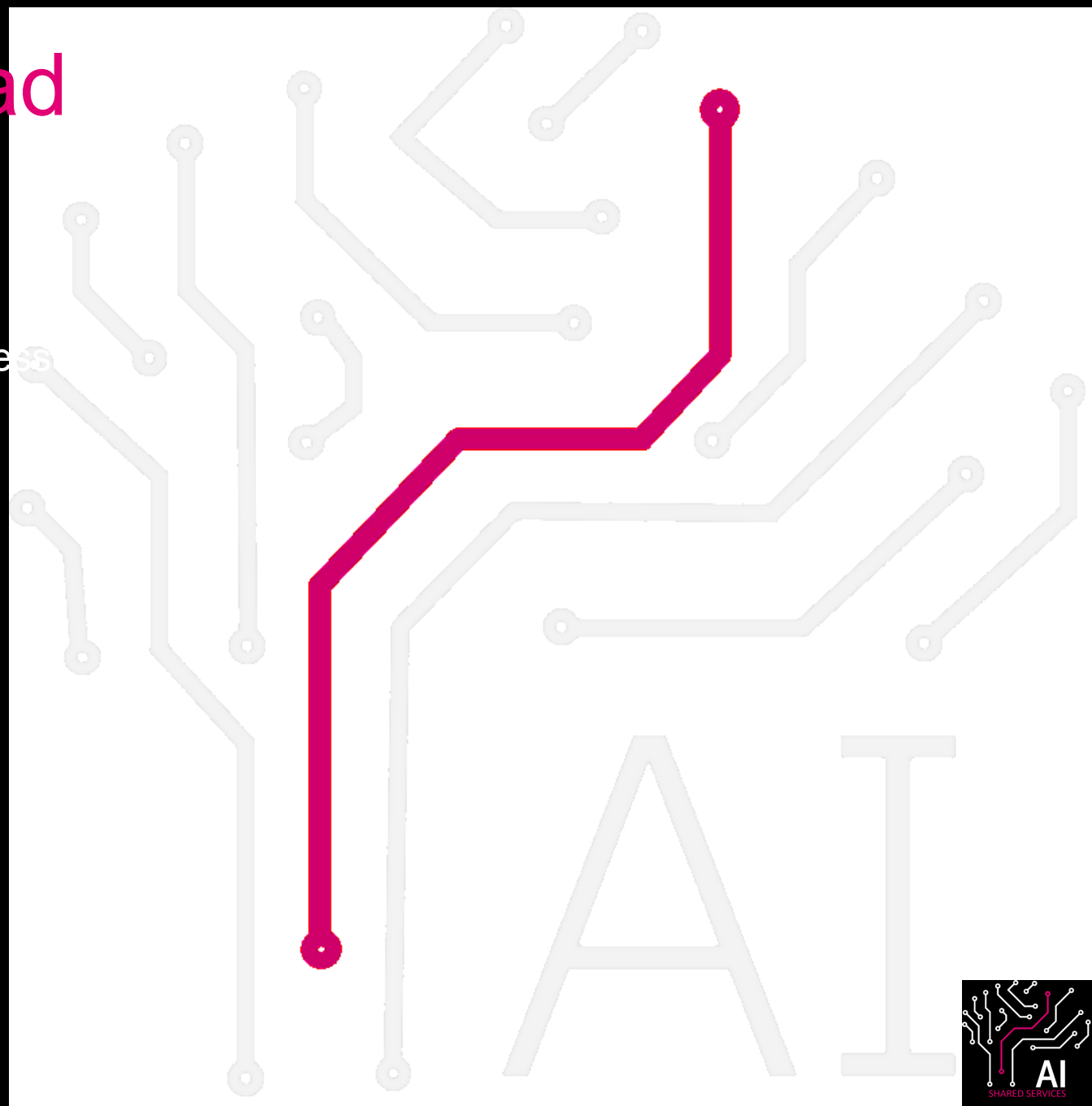
- Zlepšená schopnost rozhodování
- Zlepšená schopnost plánování
- Konkurenční výhoda
- Řízení rizika



# Predikce časových řad

## ▪ Konvenční postup:

1. Definice problému
2. Sběr dat a získávání insights od business
3. EDA – vizualizace, popisné statistiky
4. Preprocessing
5. Výběr modelů a jejich hyperparametrů
6. Cross-validace
7. Výběr finálního modelu (ensembling?)
8. Predikce
9. Postprocessing
10. Delivery



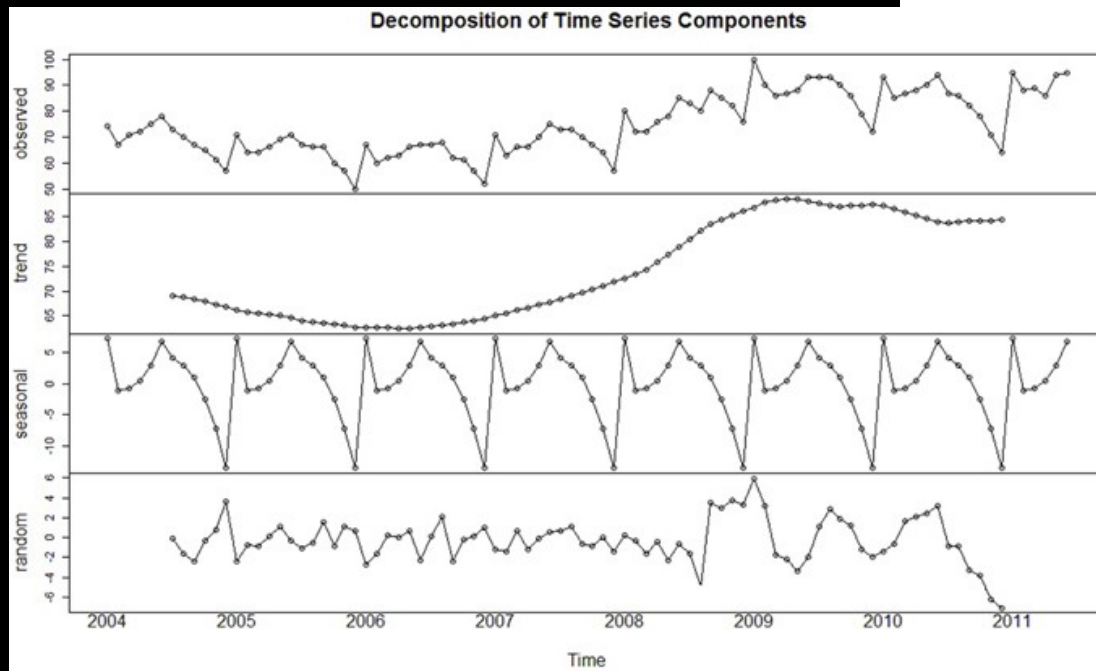


# Komponenty časových řad

Revenues [babickine\_halusky ™]



# Komponenty časových radov

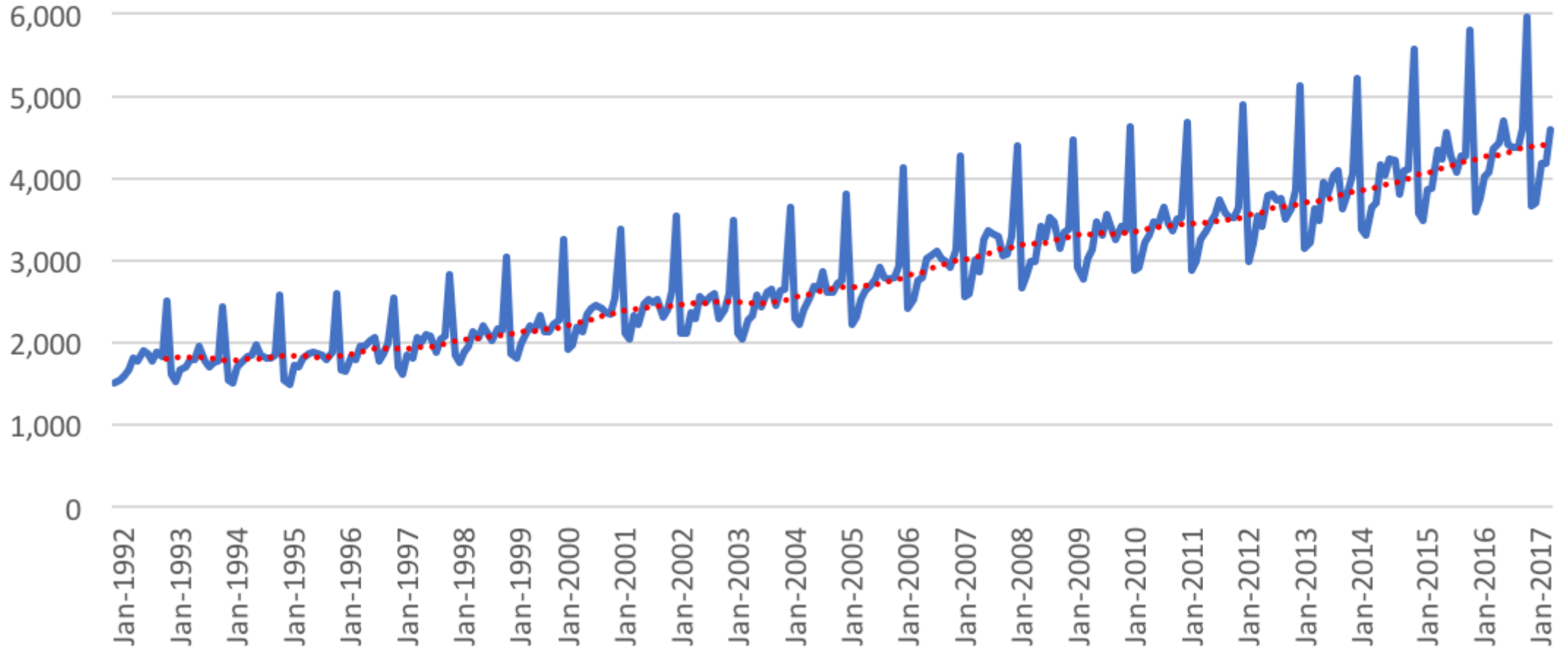


**Trend**  
**Seasonality**  
**Residuals**

# Monthly Sales in U.S. Beer, Wine and Liquor Stores 1992-2017

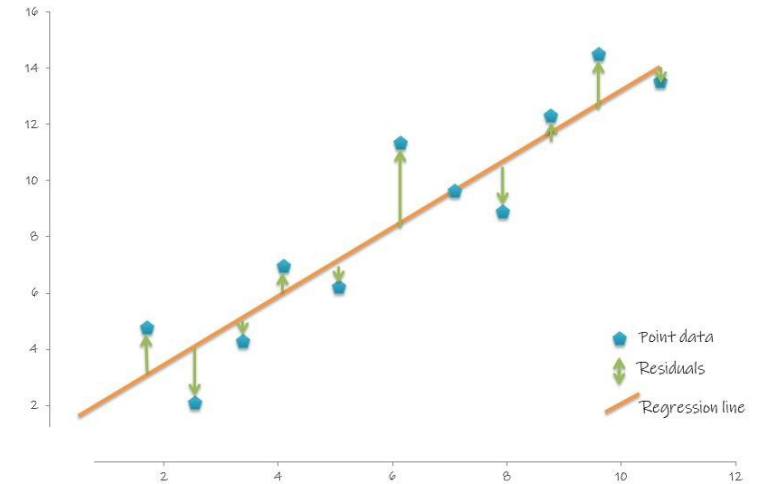
in million US\$/month (NAICS 4453), dotted line: mov 12-month avg

Source: Bureau of Census



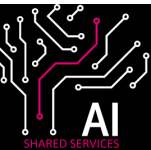
# Chyba predikce

$$e_t = y_t - \hat{y}_t$$



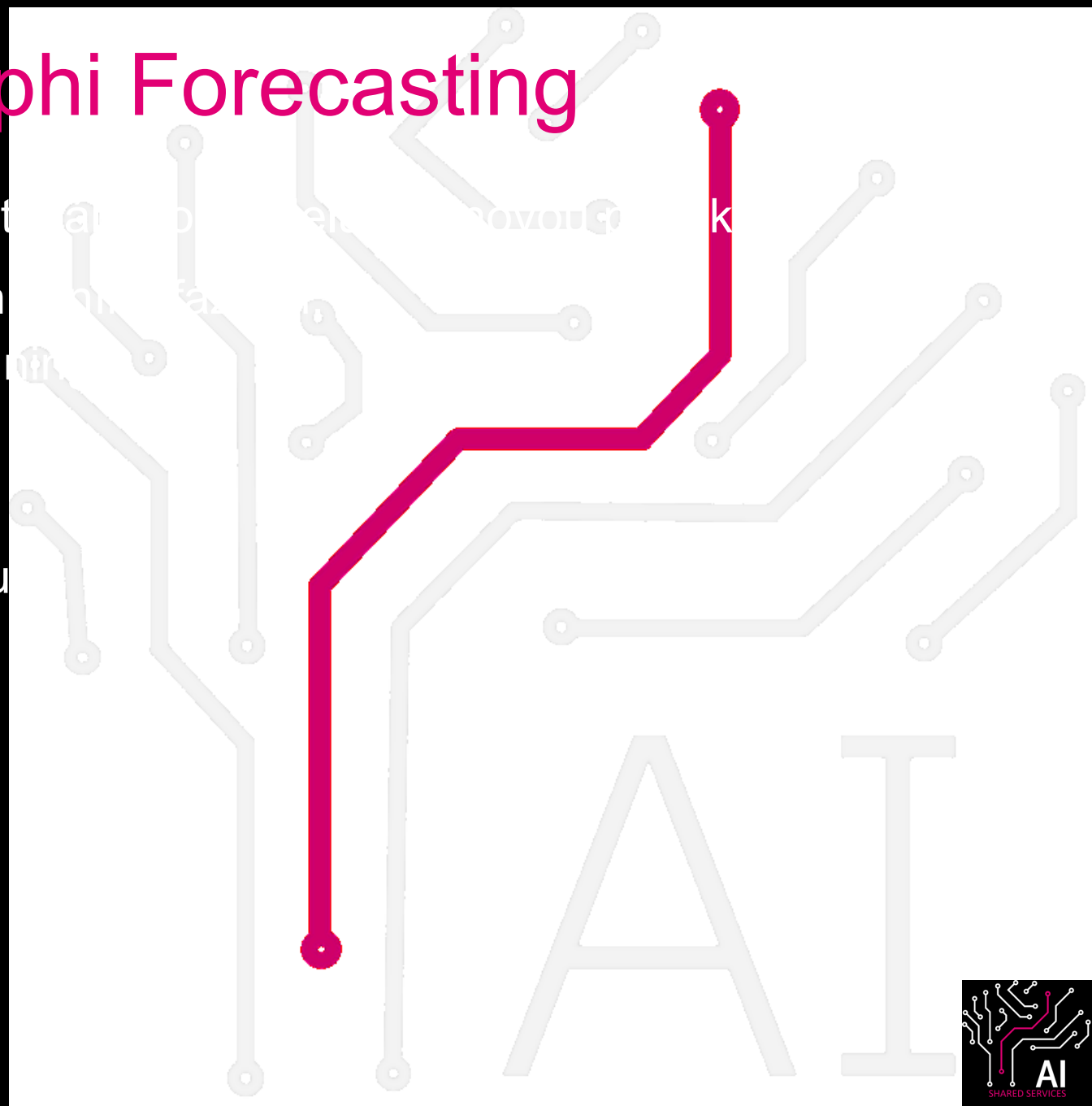
## Common error metrics:

- MAE (Mean Absolute Error)  $MAE = \text{mean}(|e_t|)$
- MSE (Mean Squared Error)  $MSE = \text{mean}(e_t^2)$
- RMSE (Root Mean Squared Error)  $RMSE = \sqrt{\text{mean}(e_t^2)}$
- MAPE (Mean Percentage Error)  $MAPE = \text{mean}(100 * e_t / y_t)$



# Auto ML řešení - Delphi Forecasting

- Každý měsíc probíhá nový výběr optimalizovaných modelů
- Delphi algoritmus prochází třemi hlavními kroky:
  - Model training ('hyperparameter tuning')
  - Model selection / evaluation
  - Prediction
- Separátně pro každou časovou řadu



# Používané technologie

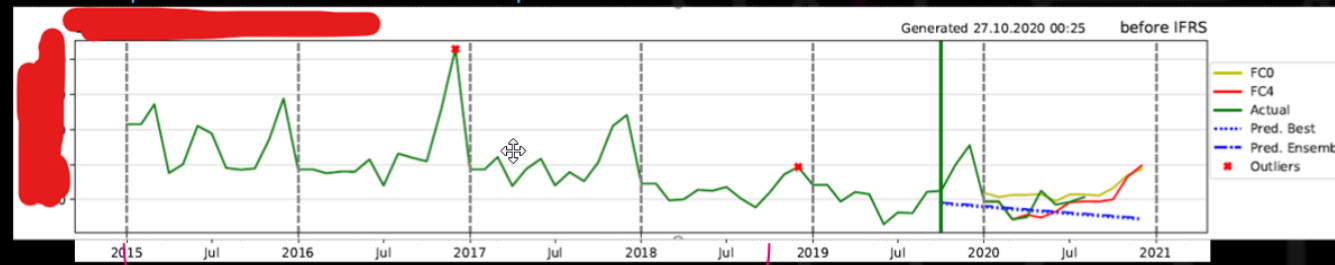
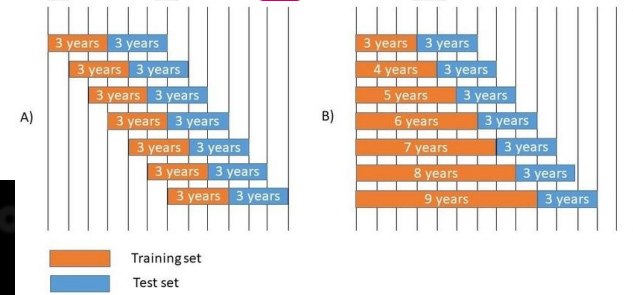
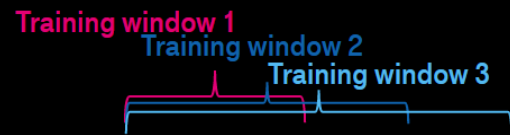


OPENS SHIFT



# Tréninování Modelu

- Každý model má hyperparametry, které s (brát vysvětlující proměnné?)
- K rychlejšímu výběru parametrů využívá (hyperparametry, které se nezdají, že by měly být důležité?)
- Model se fituje na základě zvolené kombinace (error metriky)



# DeIPy TDG Live demo

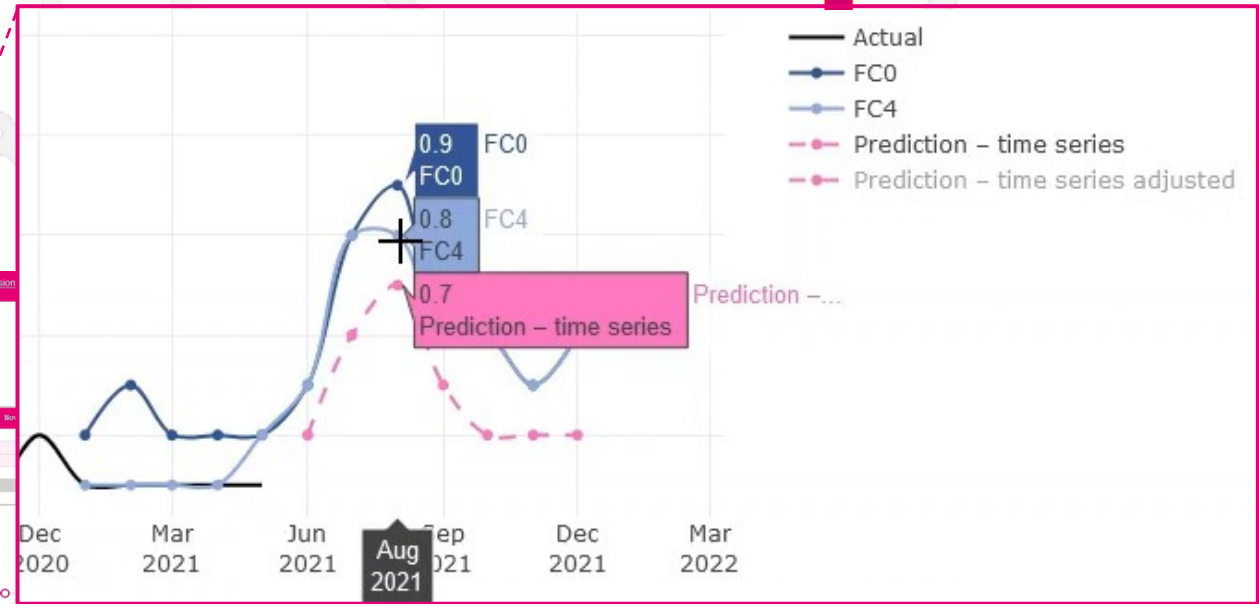
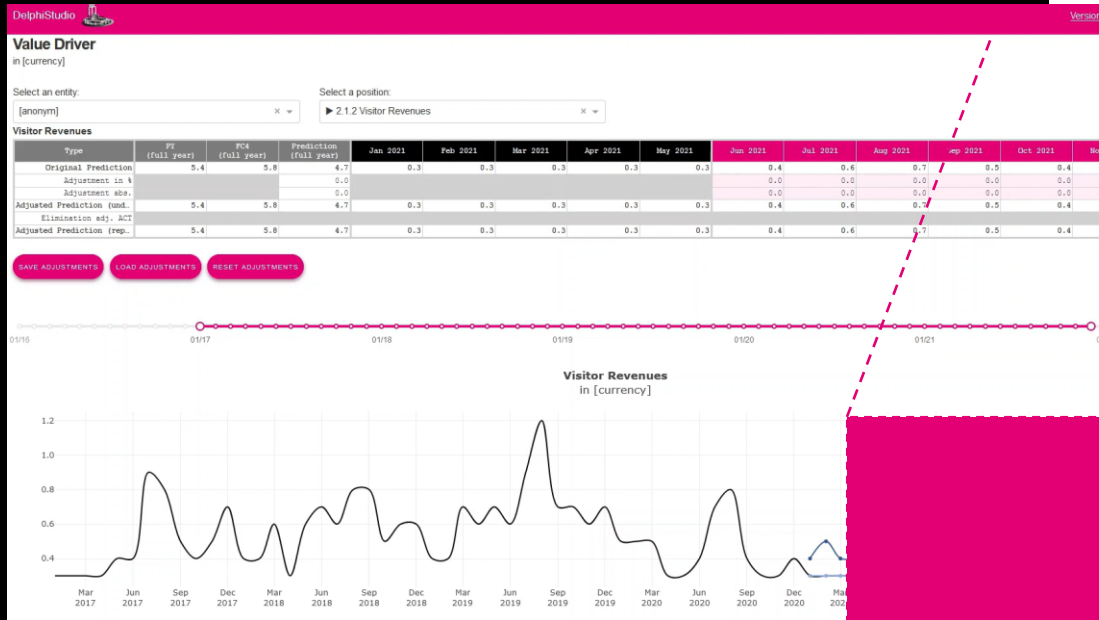


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# Delphi Studio tour (1/3): allows to visualize and compare historical, forecasted, and adjusted data



# Delphi Studio tour (2/3): adjust forecast to arrive at ML-assisted expert projection

Type	Aug 2021
Original Prediction	0.7
Adjustment in %	0.0
Adjustment abs.	0.2
Adjusted Prediction (und..	0.9
Elimination adj. ACT	
Adjusted Prediction (rep..	0.9



# Delphi Studio tour (3/3): switch between various P&L positions

Select a position:

- ▶ 2.1.2 Visitor Revenues
- ▶ 2.1 Mobile Service Revenues
- ▼ 2.1.1 Mobile ARPU Revenues
- ▶ 2.1.2 Visitor Revenues
- ▶ 2.1.3 Other Mobile Service Revenues
- ▶ 2.2 Mobile Handset
- ▶ 2.3 Other Mobile Revenues

DelphiStudio Version: 23.0.0

Value Driver  
in [currency]

Select an entity:  
[anonym]

Visitor Revenues

Type	FT (full year)	FC4 (full year)	Pre (full year)	2021	May 2021	Jun 2021	Jul 2021	Aug 2021	Sep 2021	Oct 2021	Nov 2021
Original Prediction	5.4	5.9		0.3	0.3	0.4	0.4	0.7	0.5	0.4	
Adjustment in %						0.0	0.0	0.0	0.0	0.0	
Adjustment abs.						0.0	0.0	0.7	0.0	0.0	
Adjusted Prediction (und.)	5.4	5.9		0.3	0.3	0.4	0.4	0.9	0.5	0.4	
Elimination obj. AC											
Adjusted Prediction (rep.)	5.4	5.9		0.3	0.3	0.4	0.4	0.9	0.5	0.4	

SAVE ADJUSTMENTS LOAD ADJUSTMENTS RESET ADJUSTMENTS

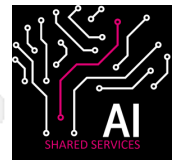
Adjustments have been saved successfully!



# ČÁST III. - Názory. Chcete někdo názory?



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# Specializace je vždy relativní

<h2>Data Scientist</h2> <p>also known as Data Managers, statisticians.</p> 	<h2>Data Engineers</h2> <p>also known as database administrators and data architects.</p> 	<h2>Data Analysts</h2> <p>also known as business Analysts.</p> 
<p>A data scientist will be able to take data science projects from end to end. They can help store large amounts of data, create predictive modelling processes and present the findings.</p> <p><i>Skills:</i> Mathematics, Programming, Communication</p>  <p><i>Will use programmes such as:</i> SQL, Python, R</p>	<p>They are versatile generalists who use computer science to help process large datasets. They typically focus on coding, cleaning up data sets, and implementing requests that come from data scientists.</p> <p><i>Skills:</i> Programming, Mathematics, Big data</p>  <p><i>Will use programmes such as:</i> Hadoop, NoSQL, and Python</p>	<p>They typically help people from across the company understand specific queries with charts.</p> <p><i>Skills:</i> Statistics, Communication, Business knowledge</p>  <p><i>Will use programmes such as:</i> Excel, Tableau, SQL</p>

# Naučte se psát kód koncepčně a tvořit úhledné projekty

- Čistý kód
- Vhodné pojmenovávání proměnných
- Modularita
- Pouze relevantní části
- Snadněji se tak buduje portfolio projektů
- Role engineeringu/architektury ML platform postupně roste – identifikace kritických částí v rámci AutoML frameworks a množství dostupných předkodu



# Neztraťte se v záplavě "cool data science"

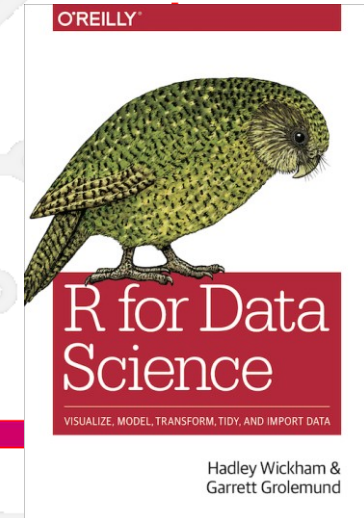
- Najděte balanc mezi užitečnými všeobecnými znalostmi a trendy
- Don't skip the basics
- Nejtěžší je získat svou první práci v oboru
- Neztraťte se v záplavě kurzů a materiálů, opravdu





# Zdroje ke studiu

- [Science as Amateur Software Development](#)
- [Value in Data Science Beyond Models in Production | RStudio](#)
- [Forecasting – Principles and Practice](#)
- [Hands on ML](#)
- [Andrew Ng Courses](#)
- [R for DS + tidyverse tutoriály](#)
  
- LinkedIn





# Závěr

- Data jsou a budou relevantní obor
- Nezapomínejte na základy - matematika, statistika
- Buďte trpěliví (při studiu, hledání práce, při práci)
- Soft skills jsou v IT někdy trochu opomíjená dovedení

OTÁZKY?