Open for Innovation
KNIME

Practicing Data Science

A Collection of Case Studies

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Greetings

- Rosaria Silipo
- Data Scientist since 1992
- Head of Evangelism at KNIME

Professional Experience

ECG Classification

Heart beats in ECG

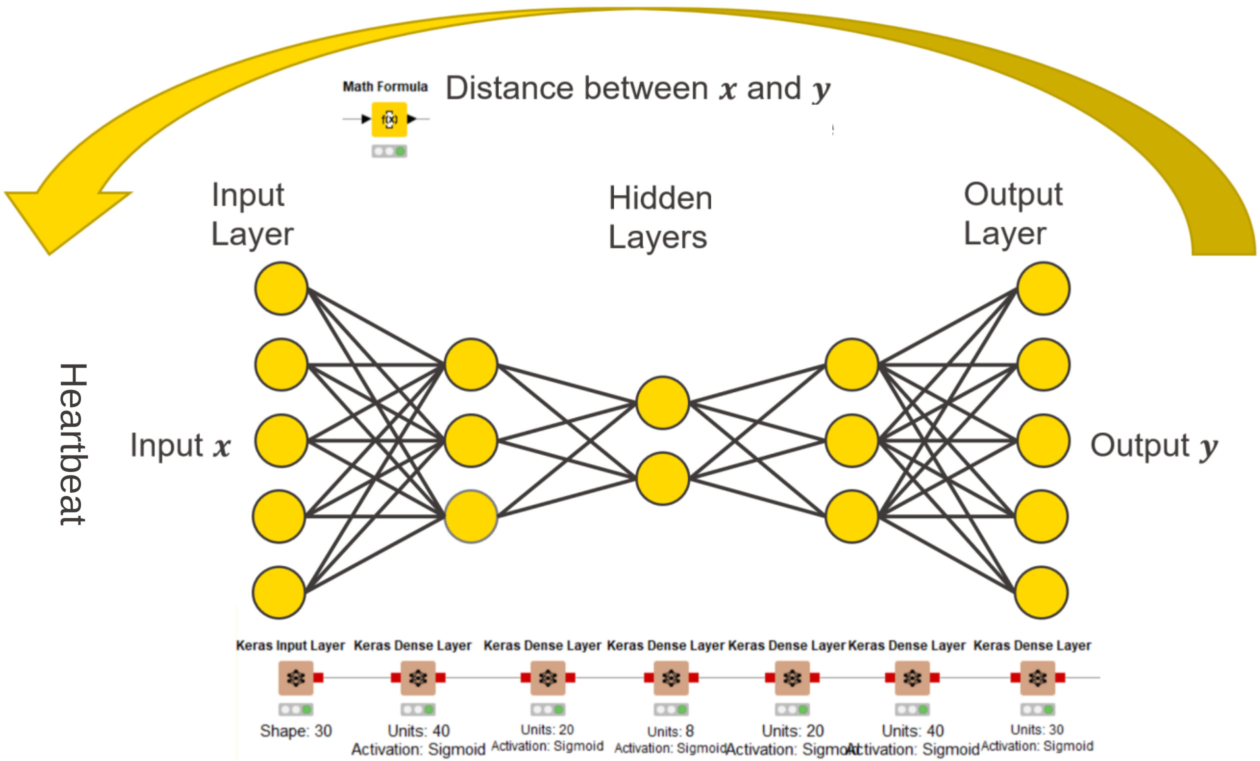
ECG signal

Model

- Sudden Arrhythmia
- Ischemic episodes
- Chronic Diseases

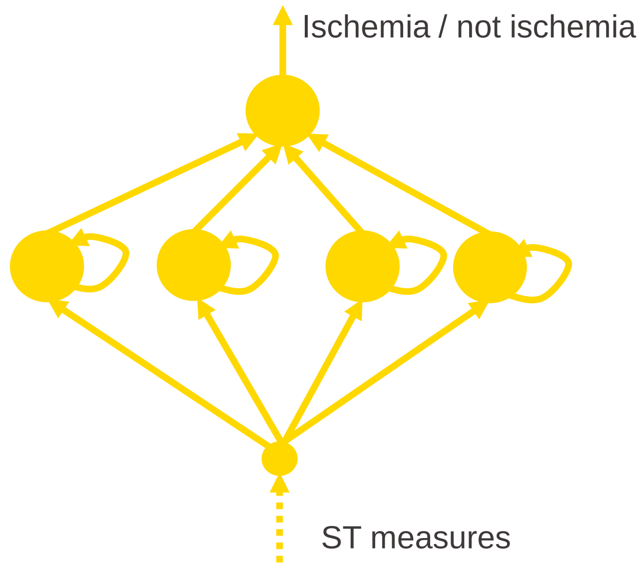
Neural Networks: autoencoder

- Sudden Arrhythmia -> anomaly detection -> neural auto-encoder



Neural Networks

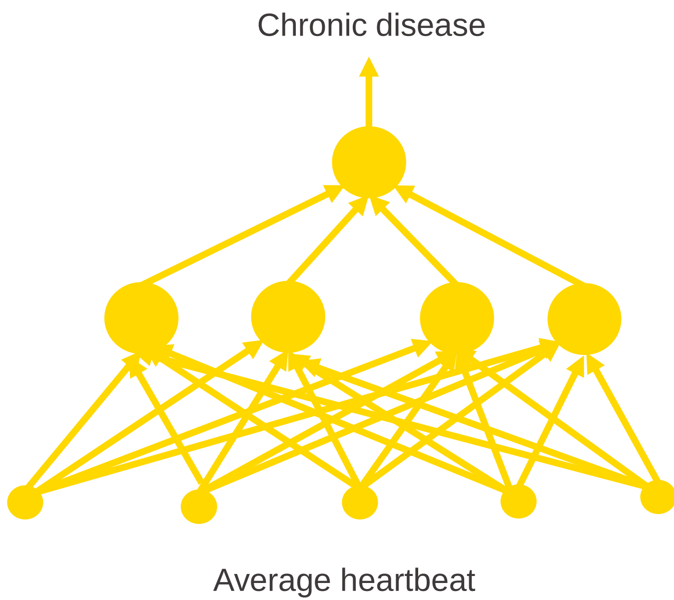
- Ischemic Episodes -> slow variation over time -> RNNs



1994

Neural Networks

- Chronic Diseases -> QRS shape clax. -> MLPs



1996

Lesson Learned

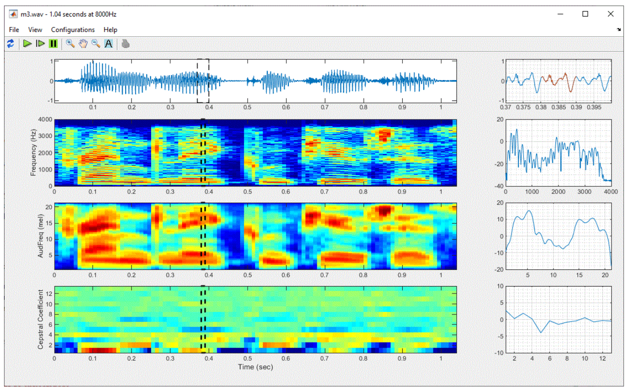
School vs. work

- 17 women out of 300 in first year EE Florence Univ.
- Competition in work environment is tougher

Signal Processing & Speech Recognition

Speech Recognition

speech signal



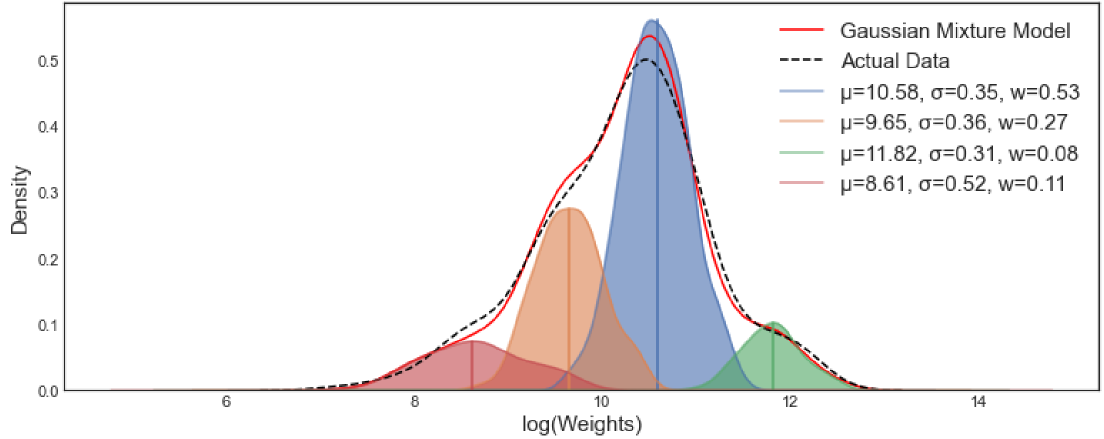
Model

Text

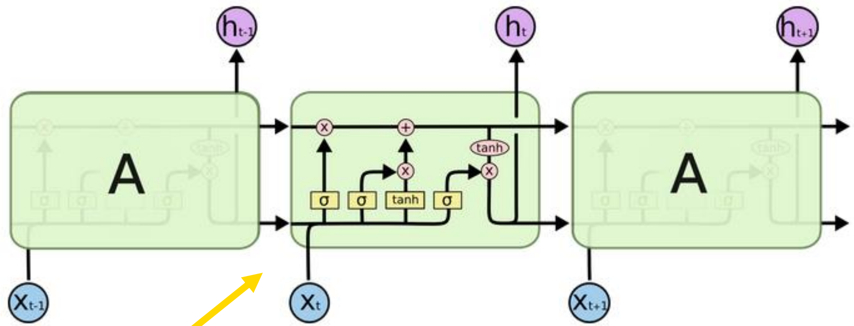
Gaussian Mixture Models

- Hidden Markov Models
- Mixture of Gaussians

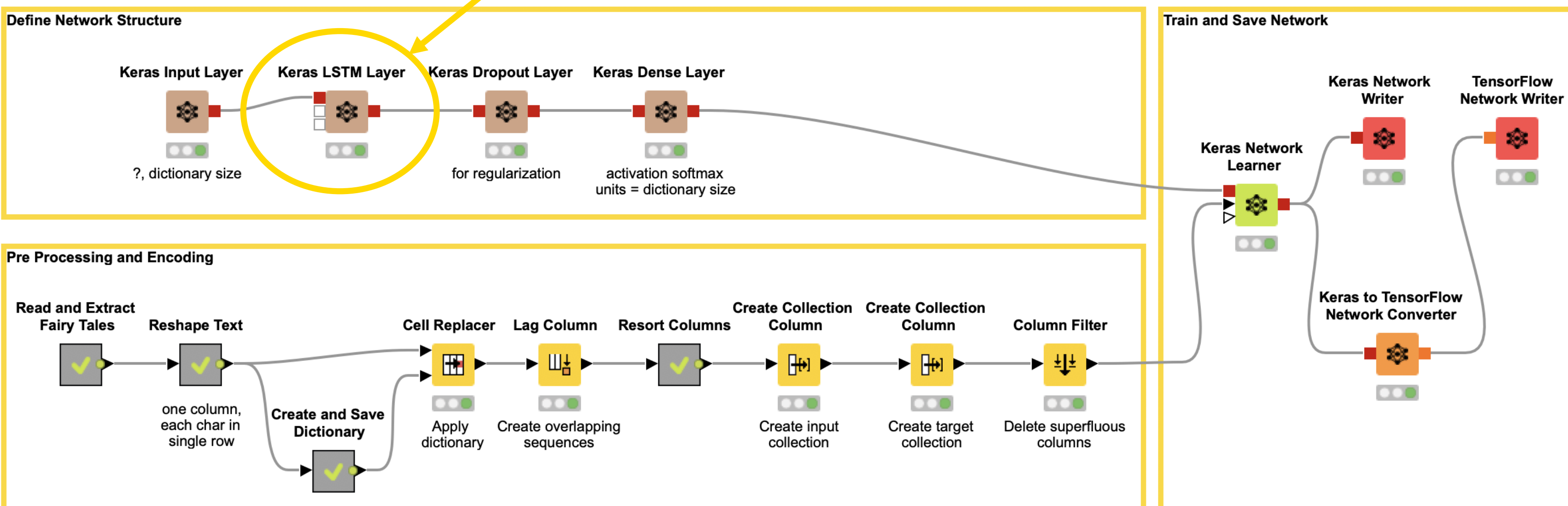
2000



LSTM Networks



2015



Lesson Learned

- First job is important
- **Great mentors are more important!**

Churn Prediction

Churn Prediction: The Problem

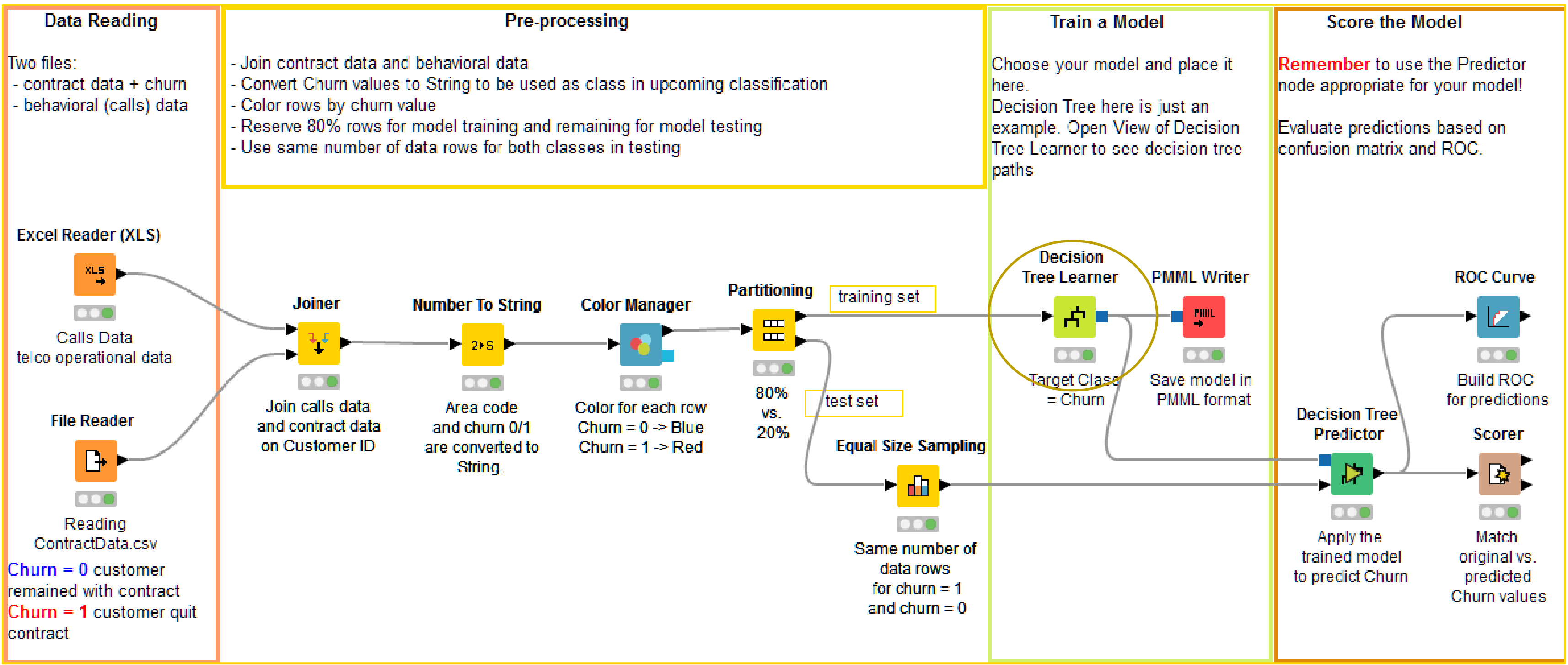
CRM System
Data about your customer

- Demographics
- Behavior
- Revenues

Model

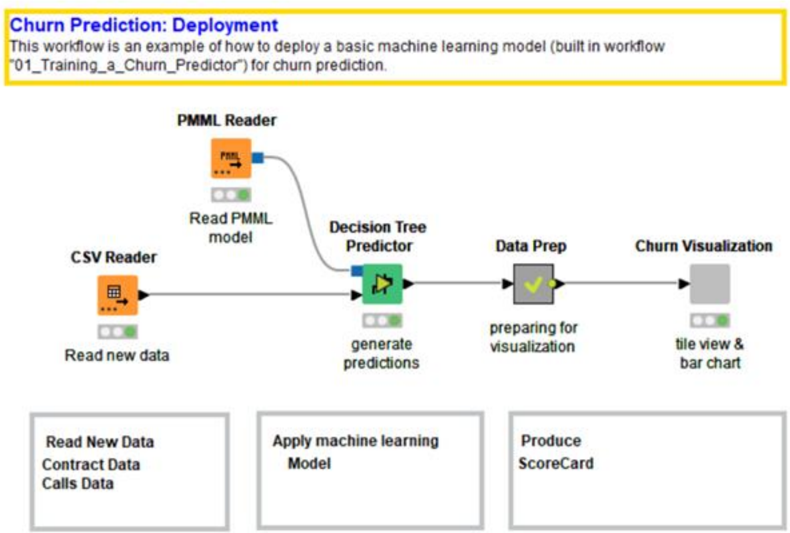
- Churn Prediction
- Upselling Likelihood
- Product Propensity /NBO
- Campaign Management
- Customer Segmentation
- …

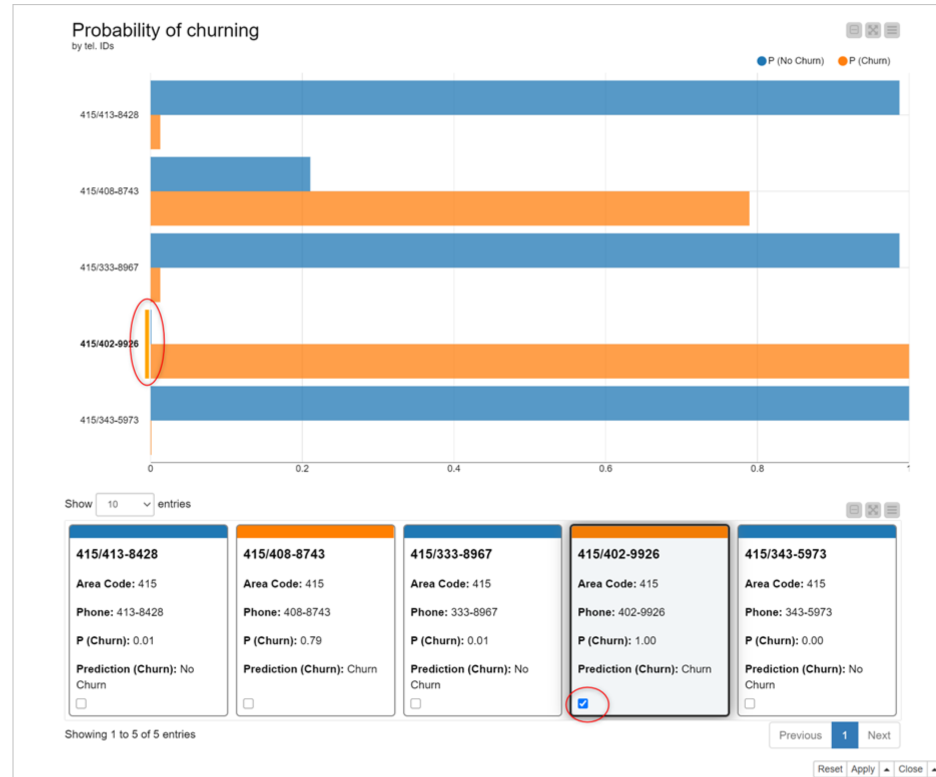
Churn Prediction: The Training Workflow



Churn Prediction: The Deployment Workflow

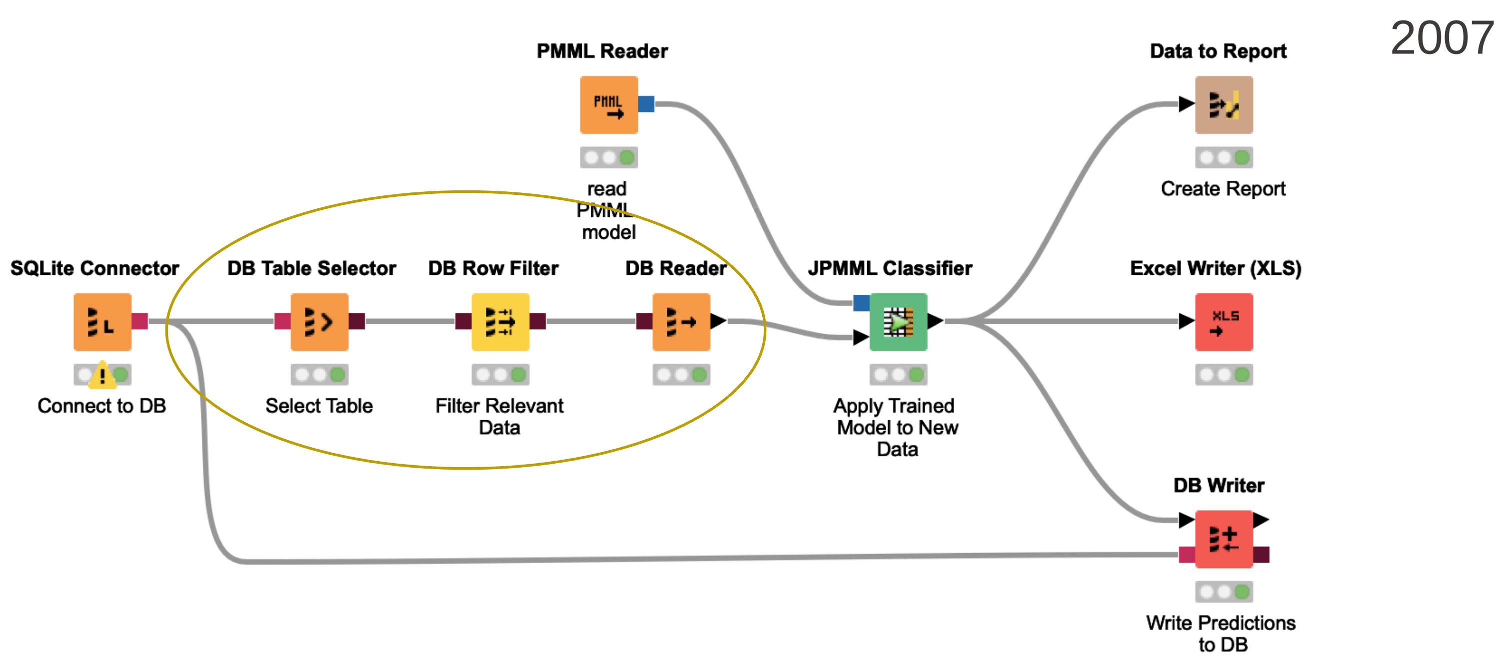
YouTube: “**Building a basic Model for Churn Prediction with KNIME”** https://www.youtube.com/watch?v=RHsO10q7e2Y



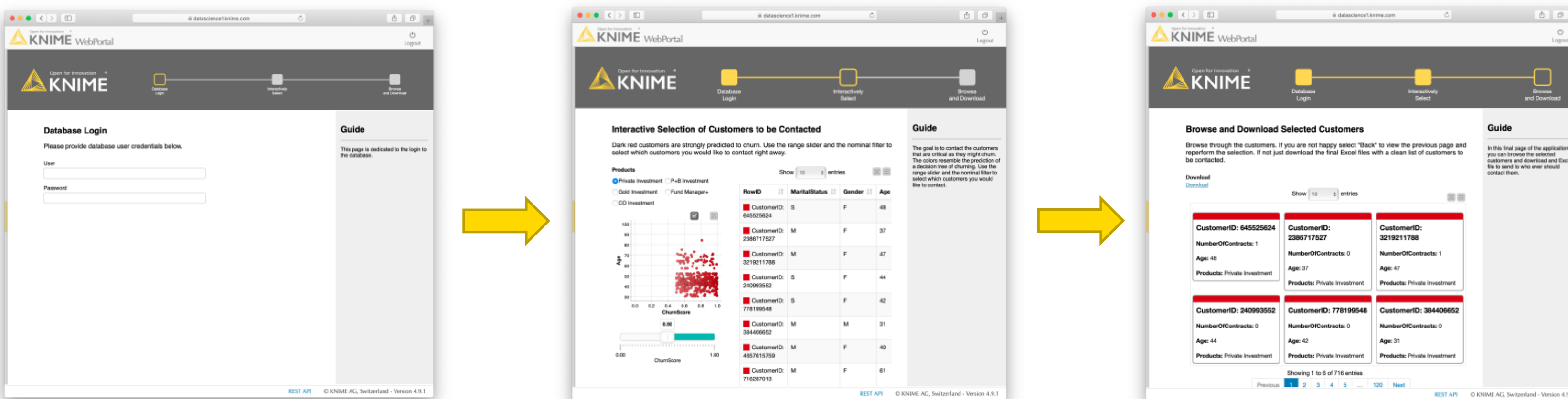


EXAMPLES Server: 50_Applications/18_Churn_Prediction

A Second Workflow for Deployment



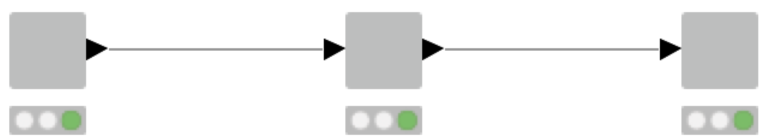
Churn Prediction: Deployment on the WebPortal



Get Customers from Database

Select Customers to Contact

Browse and Download Customers List



2007

Lesson Learned

- Motherhood and Career

ETL for Banks: ARR Calculation

Annual Recurring Revenues

Contracts

File Table - 3:1524 - Excel Reader (Read demo data)

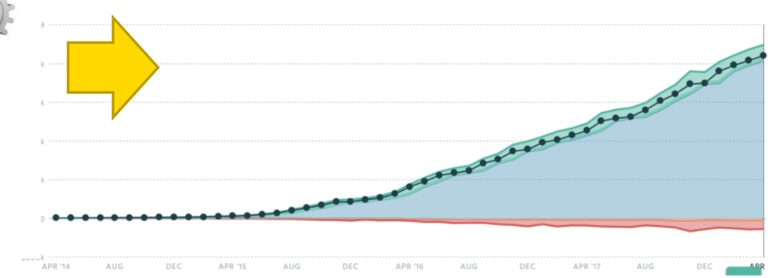
File Edit Hilite Navigation View

Table "default" - Rows: 45 | Spec - Columns: 4 | Properties | Flow Variables

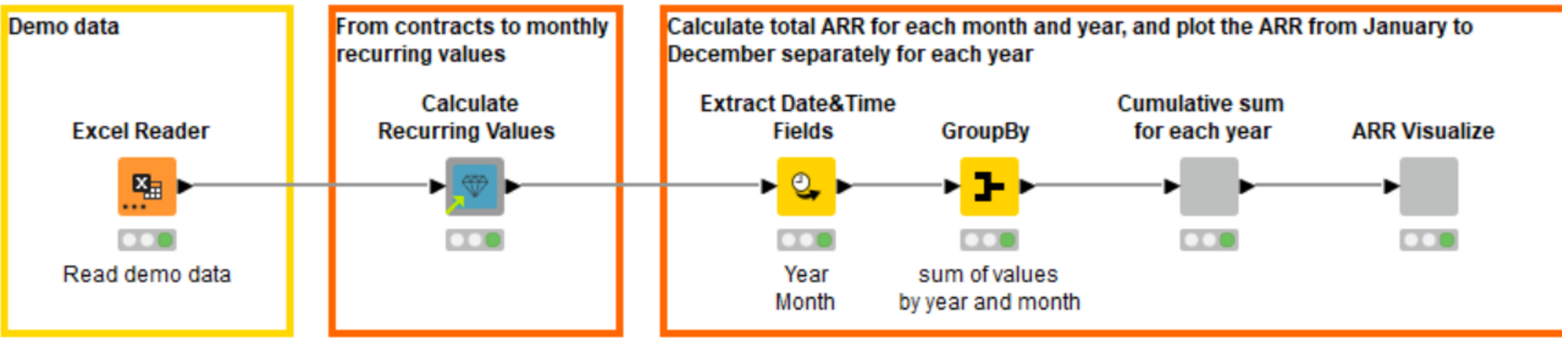
Row ID	CustID	Value	Start	End
Row0	Anton	10000	2015-01-01	2015-12-31
Row1	Anton	6700	2016-01-01	2016-08-31
Row2	Anton	2000	2016-09-01	2016-12-31
Row3	Anton	12000	2017-01-01	2017-12-31
Row4	Anton	20000	2018-01-01	2018-12-31
Row5	Anton	20000	2019-01-01	2019-12-31
Row6	Horst	5000	2015-07-01	2015-12-31
Row7	Horst	5000	2016-01-01	2016-06-30
Row8	Horst	2000	2016-07-01	2016-12-31
Row9	Horst	4000	2017-01-01	2017-06-30
Row10	Horst	6000	2017-07-01	2017-12-31
Row11	Horst	12000	2018-01-01	2018-12-31
Row12	Horst	12000	2019-01-01	2019-12-31
Row13	Otto	4000	2015-09-01	2015-12-31
Row14	Otto	8000	2016-01-01	2016-08-31
Row15	Thomas	7000	2016-01-01	2016-06-30
Row16	Thomas	10000	2016-07-01	2016-12-31
Row17	Thomas	17000	2017-01-01	2017-12-31
Row18	Thomas	10000	2018-01-01	2018-12-31
Row19	Thomas	10000	2019-01-01	2019-12-31

Model

ARR

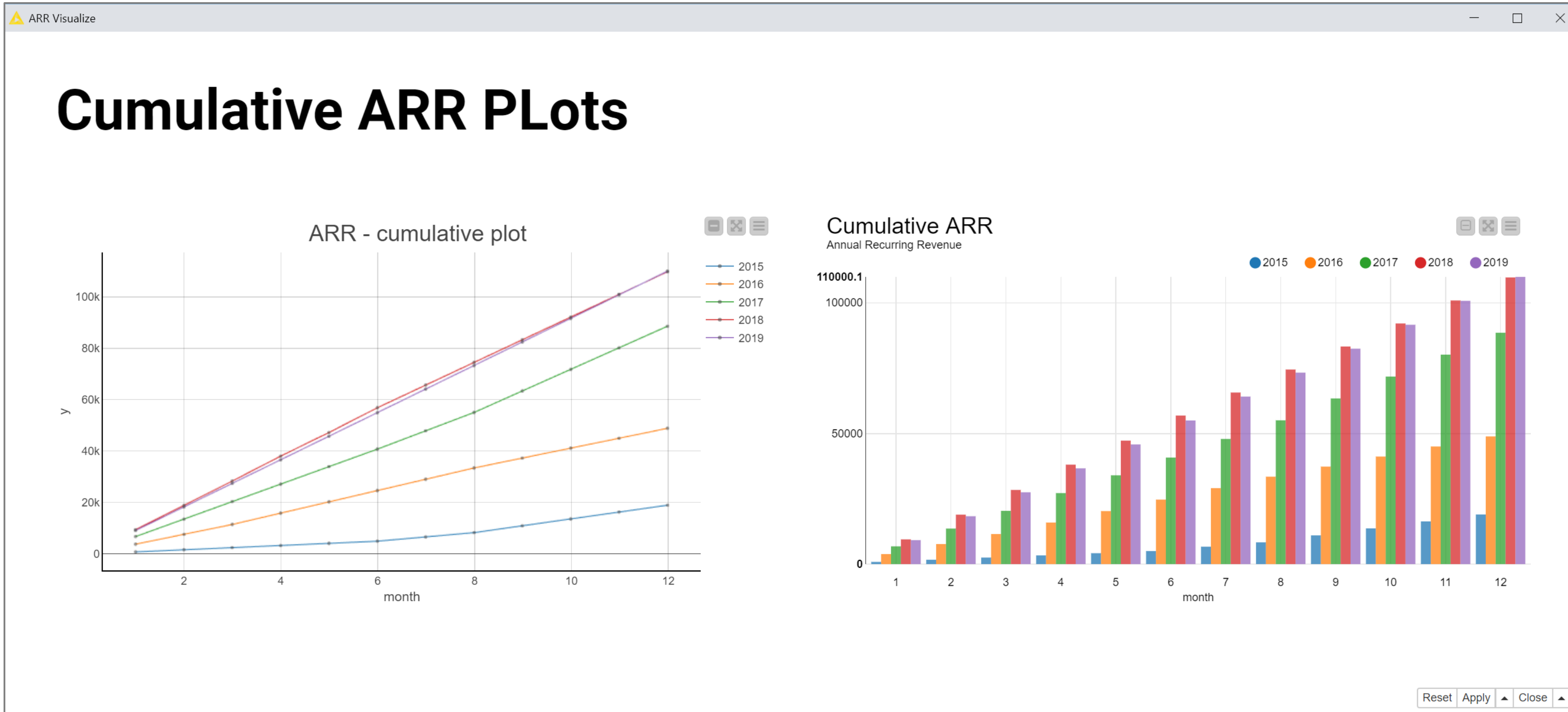


Annual Recurring Revenues



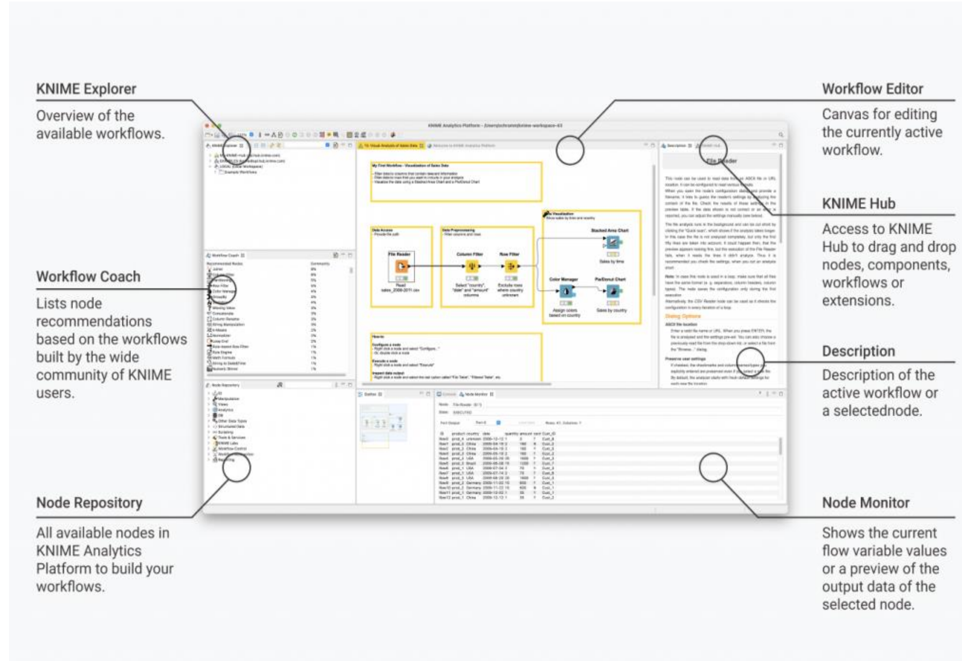
2009

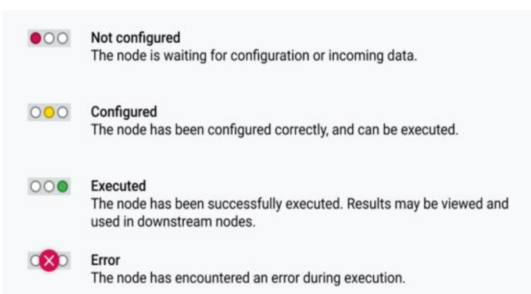
ARR final page



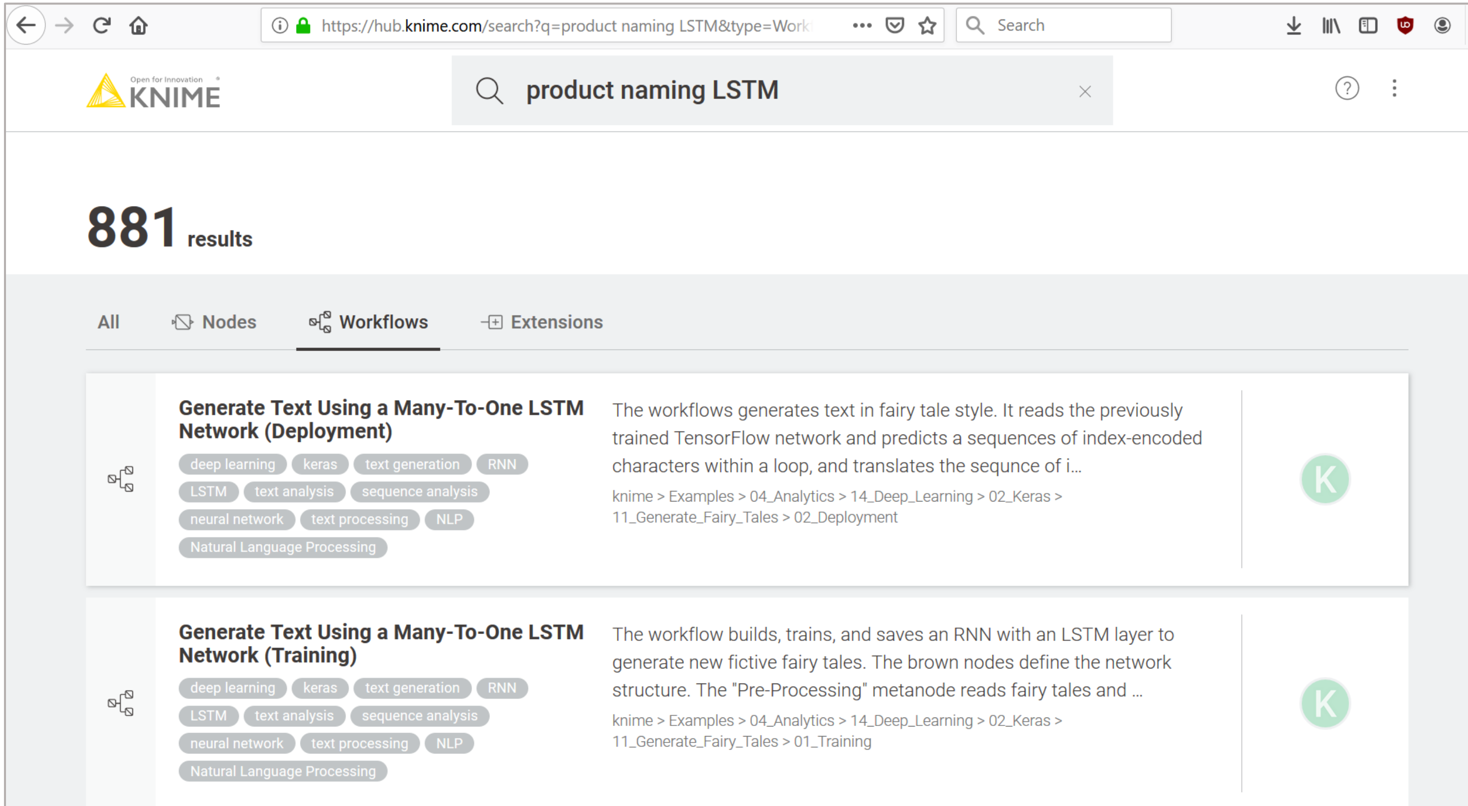
Lesson Learned

- This is when I first got to know KNIME
- Open Source
- Low Code
- Large Coverage
- Active Community
- Examples on KNIME Hub
- Support on KNIME Forum





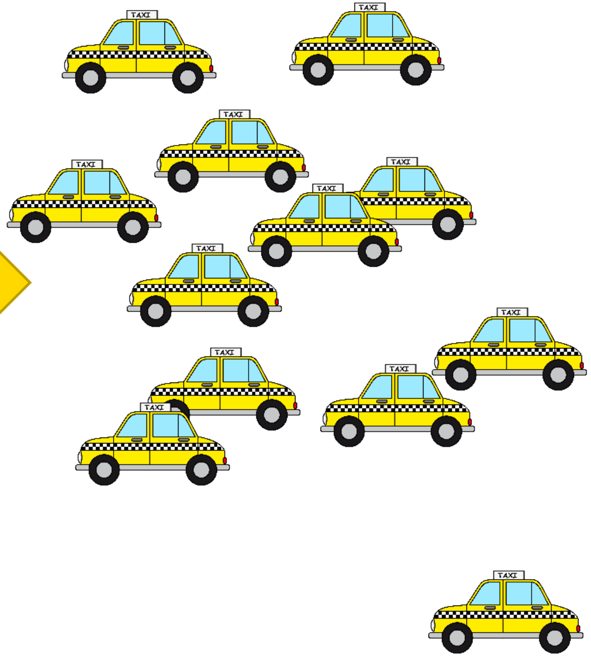
KNIME Hub (https://hub.knime.com)



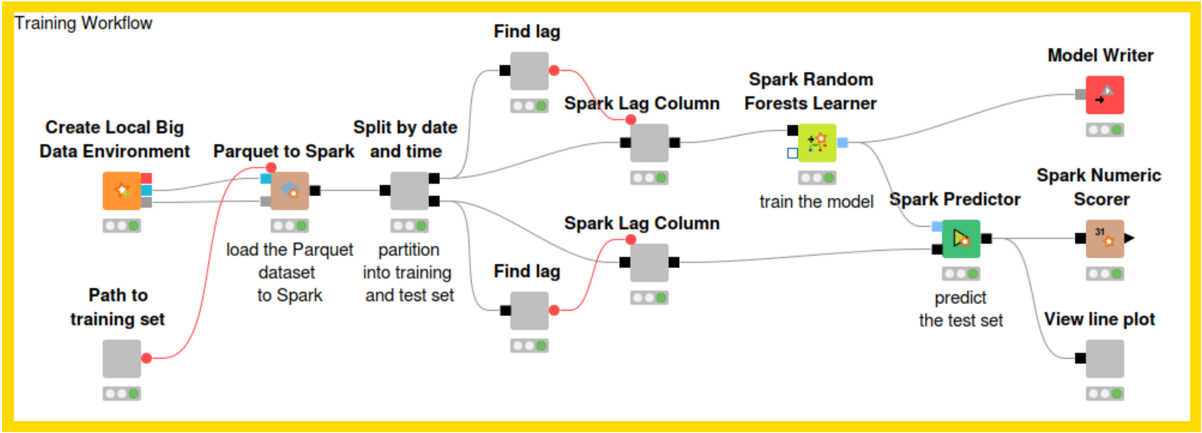
Demand Prediction (Taxi)

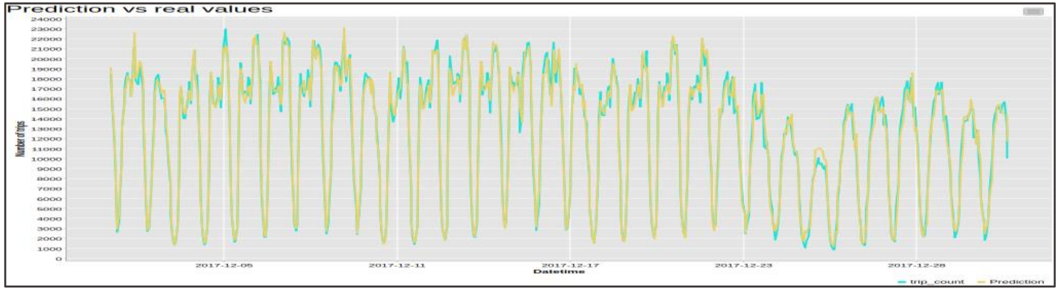
Demand Prediction: The Problem

How many taxi do I need in NYC on Wednesday at 12:00?

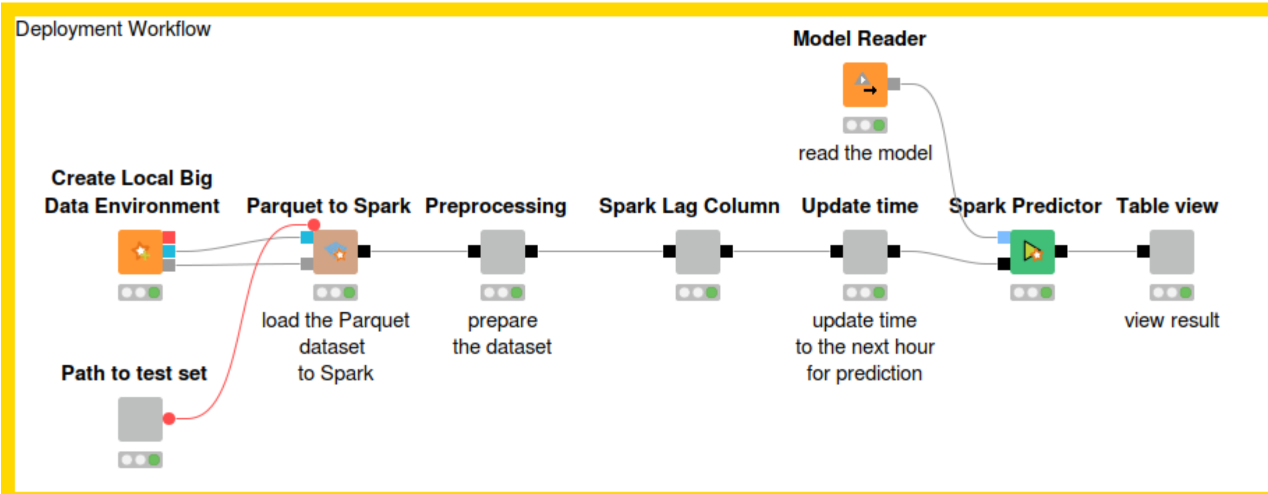


Demand Prediction: The Training Workflow





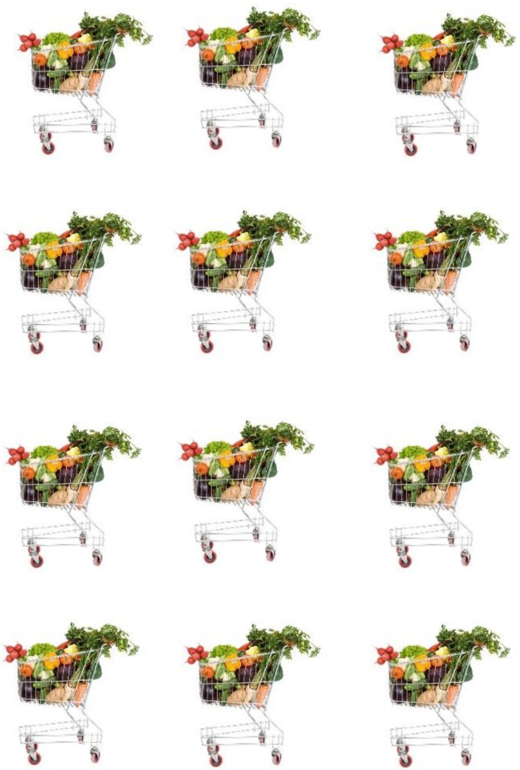
Demand Prediction: Deployment



On Wednesday at 12:00 we need **60k taxis**

Recommendation Engines

Recommendation Engines or Market Basket Analysis



Model

$$Rule:\ X \Rightarrow Y$$

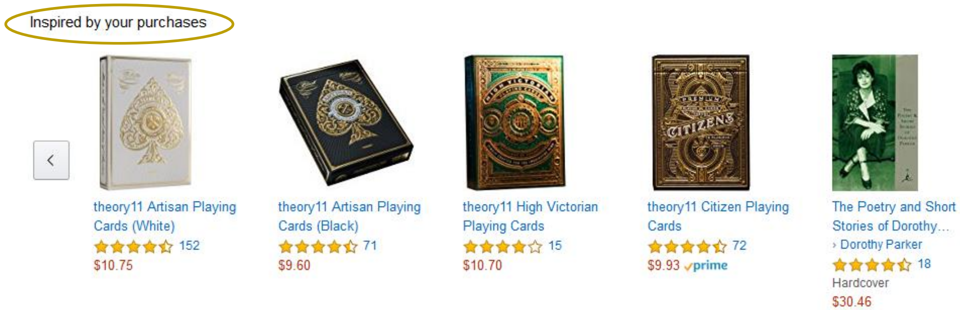
$$Support = \frac{frq(X,Y)}{N}$$

$$Confidence = \frac{frq(X,Y)}{frq(X)}$$

$$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$$

Recommendation

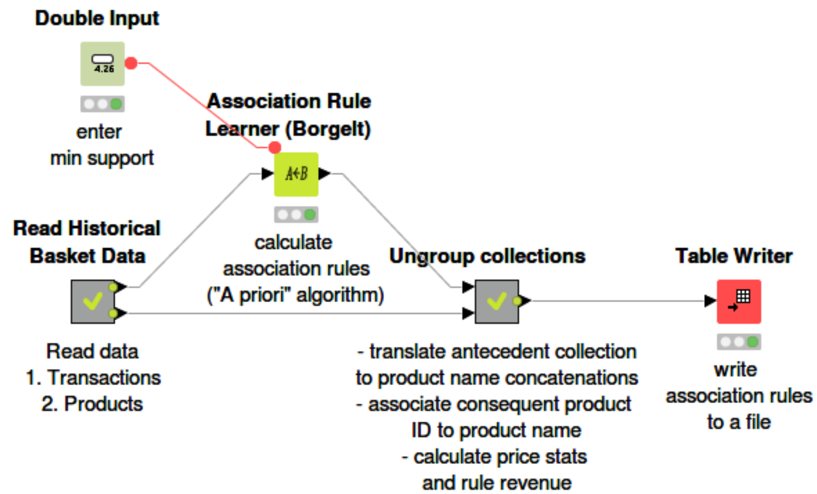
IF  => 



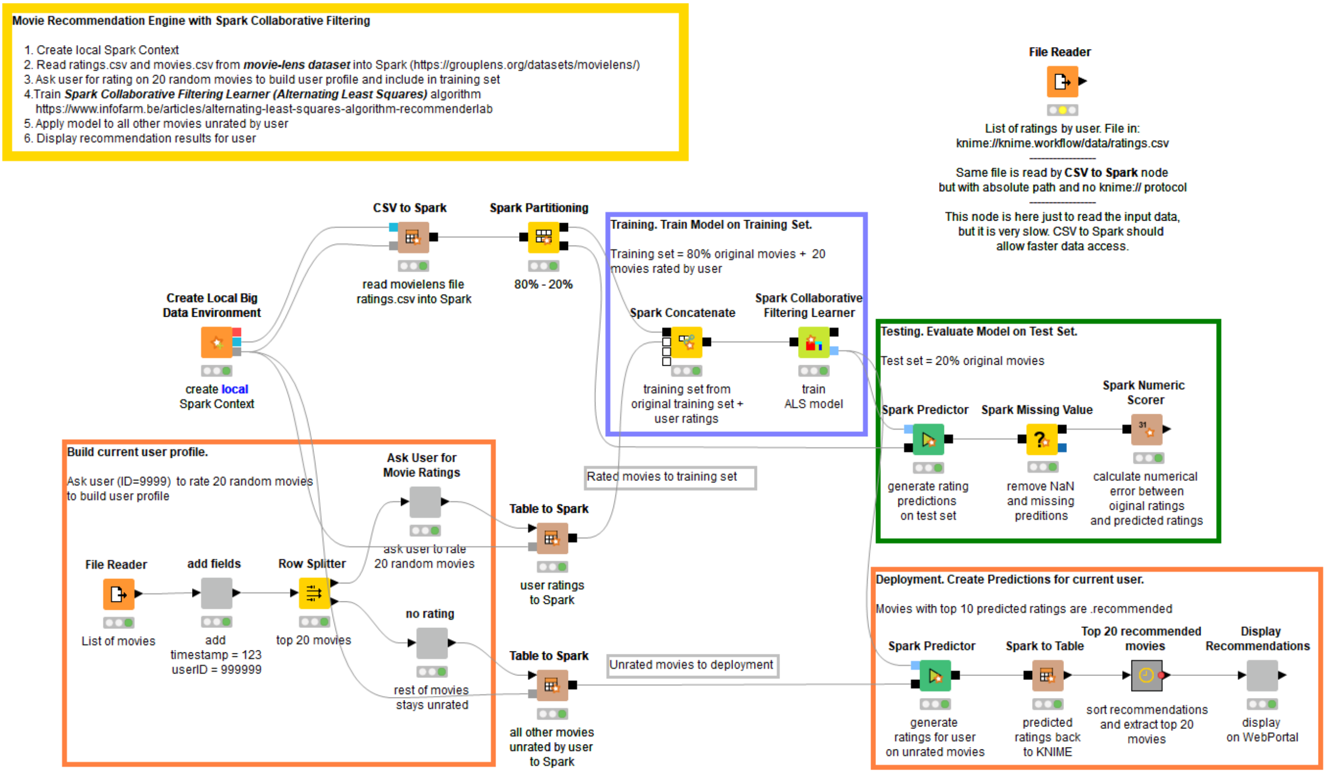
Market Basket Analysis: with Association Rules

Market Basket Analysis: Build Association Rules

1. Read Transaction/Basket data and Product data
2. Using "A priori" algorithm, build association rule set
   - min. set size = 1
   - min rule confidence = 10%
   - min support is controlled by Double Input Quickform node in %
3. Translate Antecedent collections into product name concatenations
4. Translate Consequent Item ID into Consequent Product Name
5. Calculate price stats and rule revenue
6. Write assciation rule set to file



Recommendation Engine: with Collaborative Filtering



Recommendation Engine/MBA: Deployment

Basket Analysis Report

Welcome to our Supermarket Chain!

The total price for your current shopping cart is **79.17**$!

Purchase Advices

1. Try our **lobster** !

Today's price for lobster is just 23.72$!

... and if you like our **shrimps**, we are sure you will also enjoy the **lobster** !

---

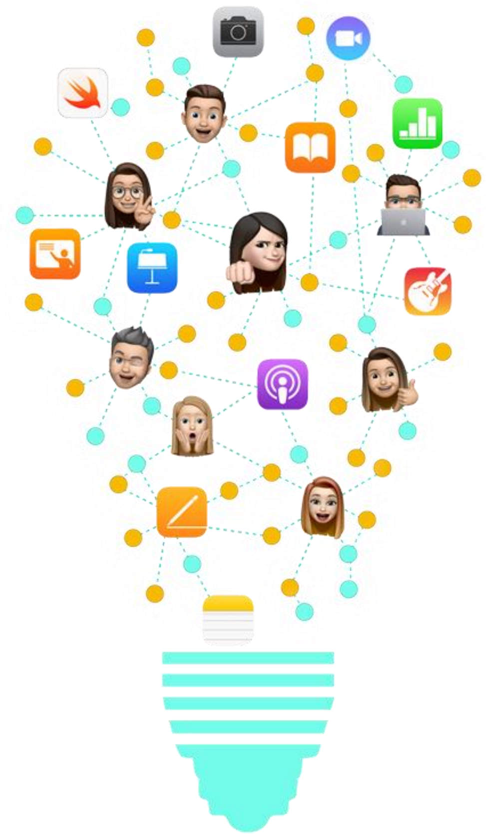
2. Try our **lobster** !

Today's price for lobster is just 23.72$!

... and if you like our **cookies**, we are sure you will also enjoy the **lobster** !

Created with KNIME Report Designer. Provided by KNIME.com AG, Zurich, Switzerland

Lesson Learned

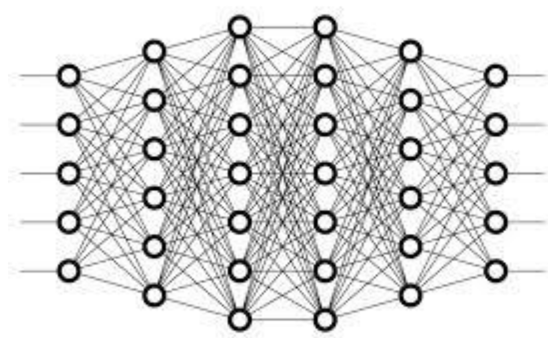


- Find a job where you can learn …

Fraud Detection

Fraud Detection

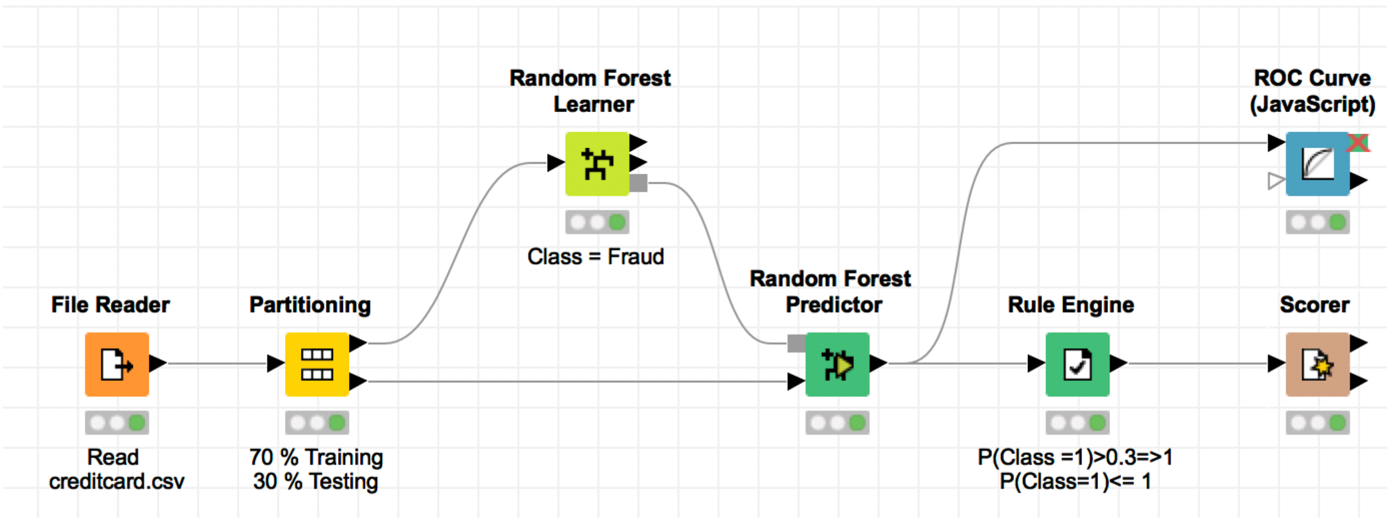
Transactions
- Trx 1
- Trx 2
- Trx 3
- Trx 4
- Trx 5
- Trx 6
- …



Model

- Good
- Good
- Good
- **Fraud**
- Good
- Good
- …

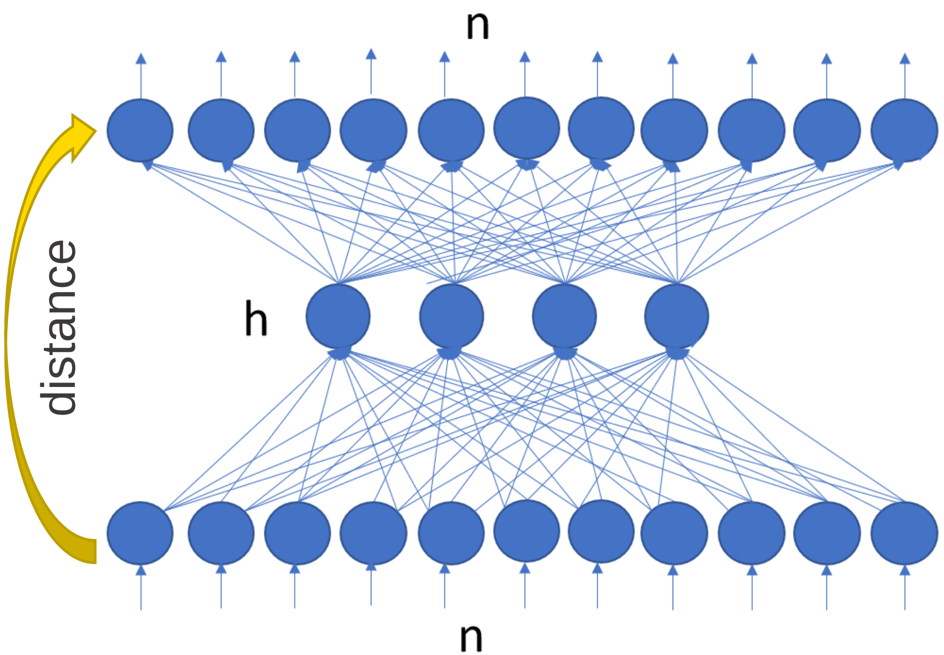
Fraud Detection with Examples



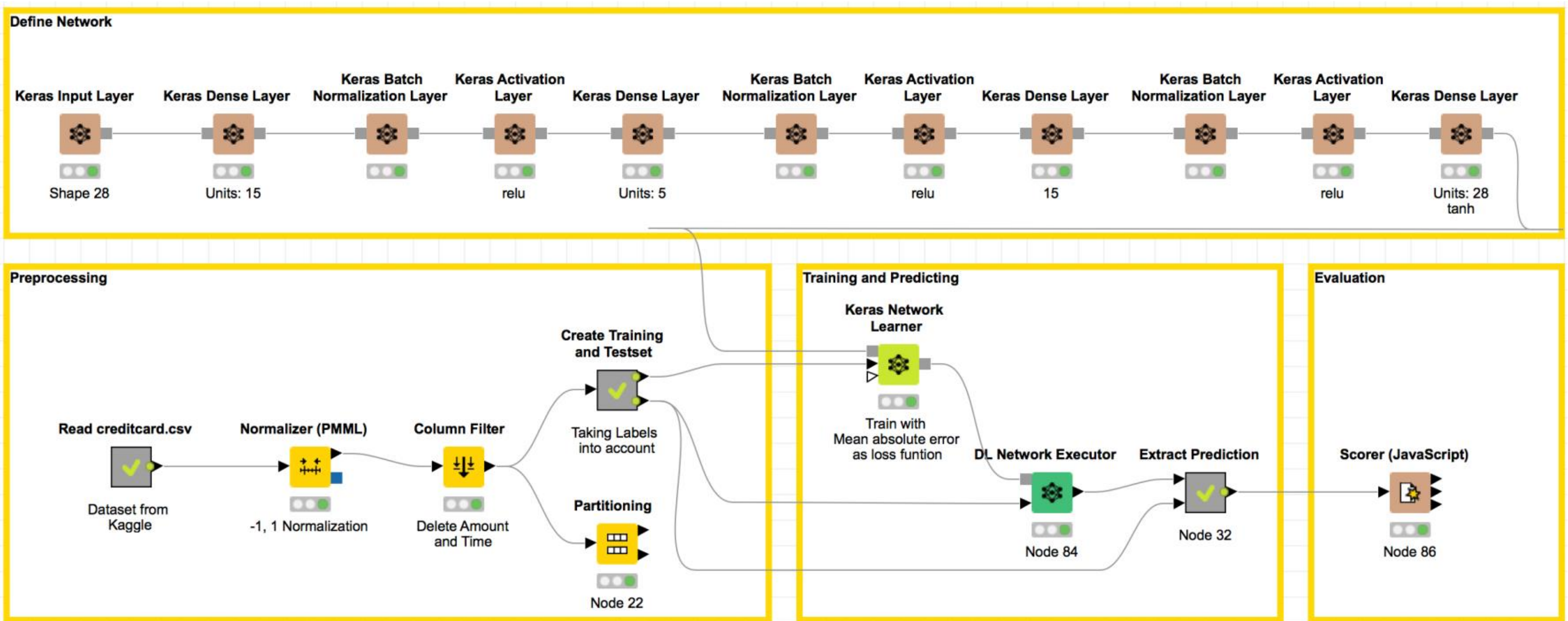
Fraud Detection: without Examples – Auto-encoder

- Trained with Back-Propagation on just “normal” transactions

- If distance > threshold => possible fraud

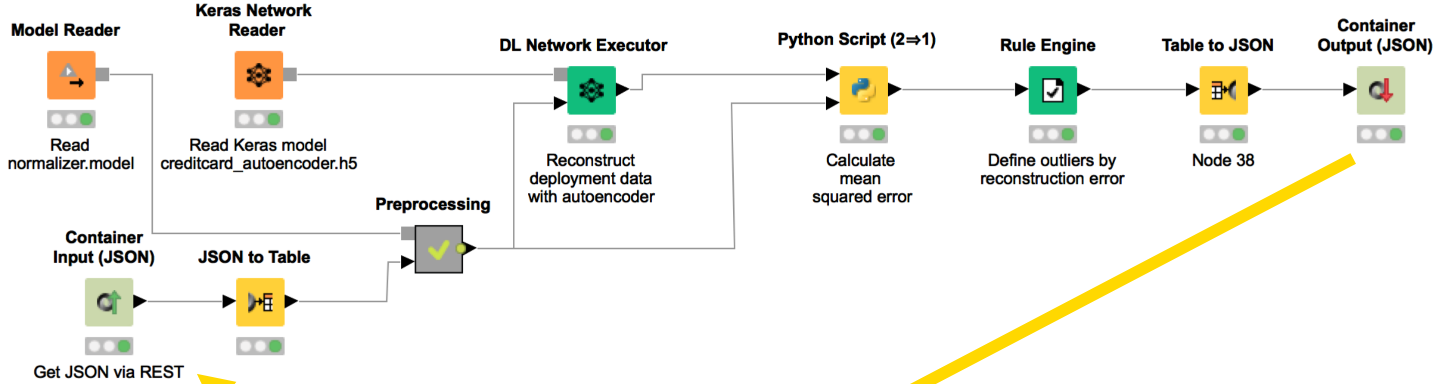


Fraud Detection without Examples

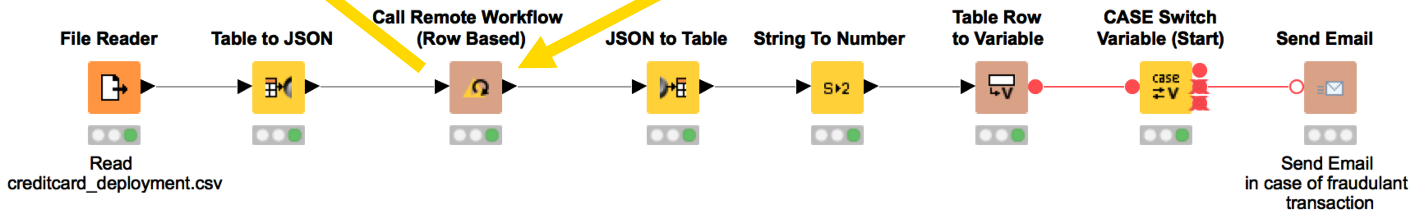


Deployment via REST on KNIME Server

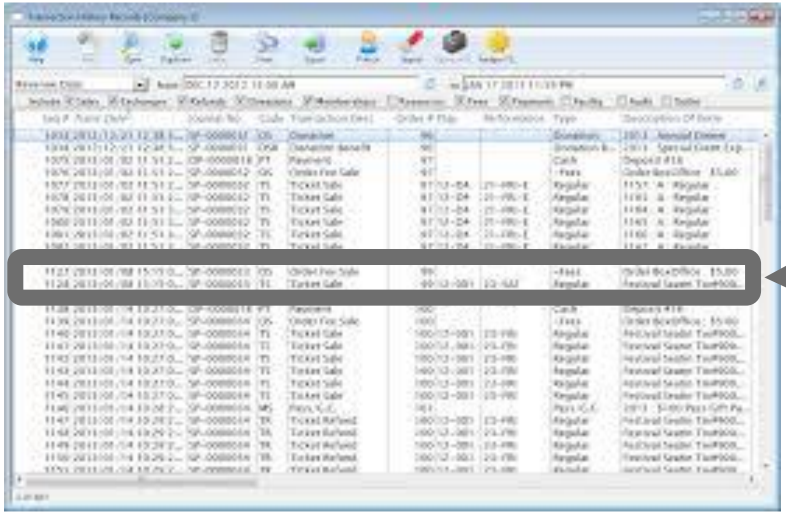
Workflow deployed as (REST) web service on KNIME Server



Workflow calling another workflow on KNIME Server



Fraud Detection deployed



Suspicious Transaction

Anomaly Detection in Predictive Maintenance (IoT)

Anomaly Detection: The Problem

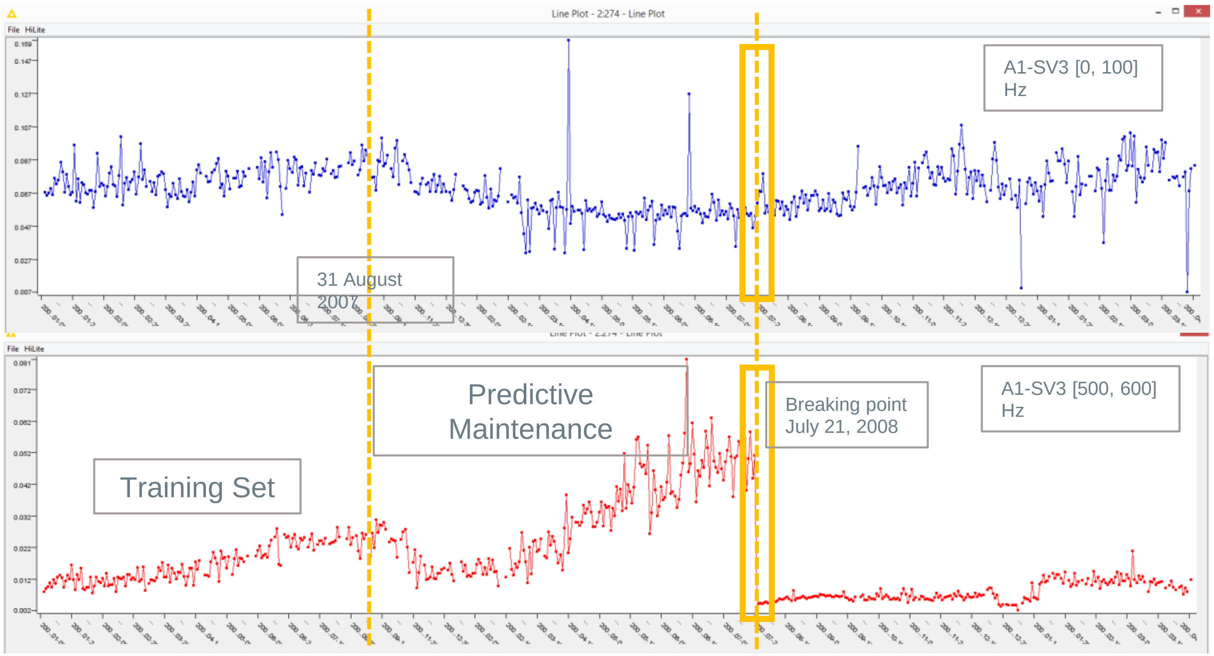
Dynamic Unsupervised Anomaly Detection

Some measures change over time till their values are not normal anymore. For example, while a motor is slowly deteriorating, one of the measurements might change till it gets out of control and the motor breaks. We want to stop the motor before it completely breaks producing even more damages

The Data: Time Series

- 28 time series from 28 sensors on 8 different parts of a mechanical engine.
- Time Series are FFT-derived Spectral Amplitudes
- There is only one motor breakdown episodes on July 21, 2008
- The breakdown is visible only from some sensors and only in some frequency bands
- The rotor was substituted with a new one after the breakdown

The Data: Time Series



Only some Spectral Time Series shows the break down

Anomaly Detection: Training

Training Set of „**normal**“ values → Build vector of past values → Train Regression Model → Save Model to file

Anomaly Detection: Deployment

New values

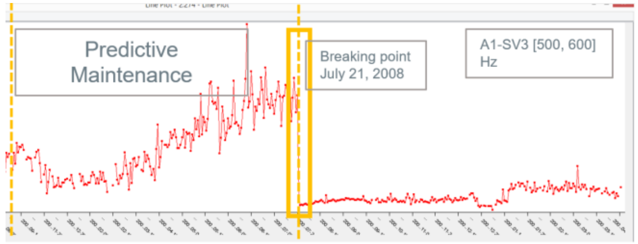
Build vector of past values

Apply Regr. Model

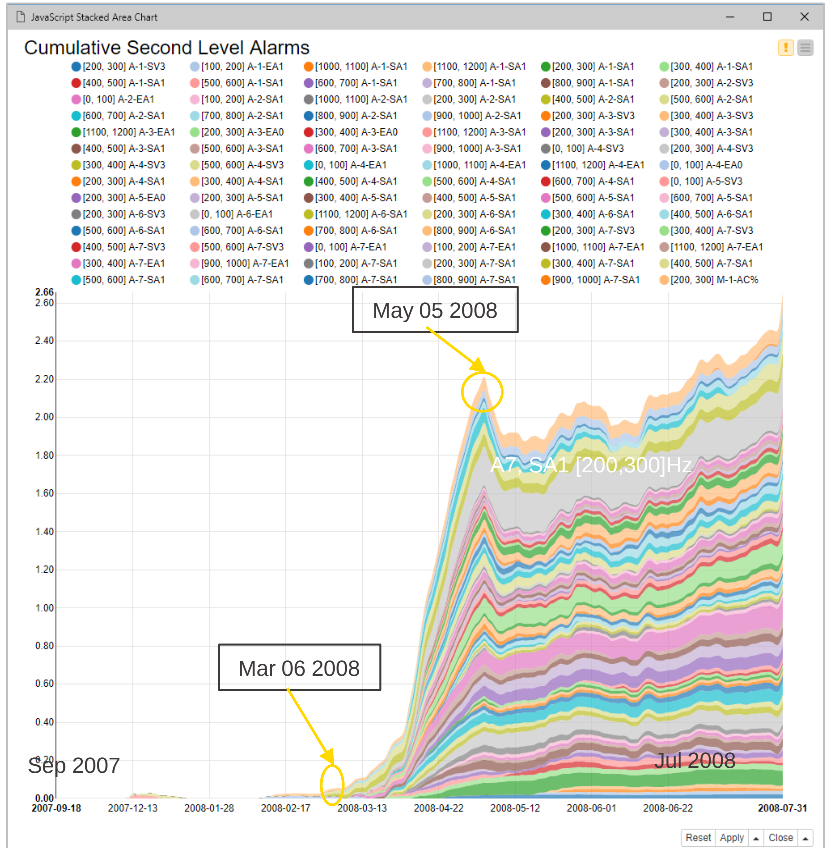
Calculate **Distance**

Moving Average

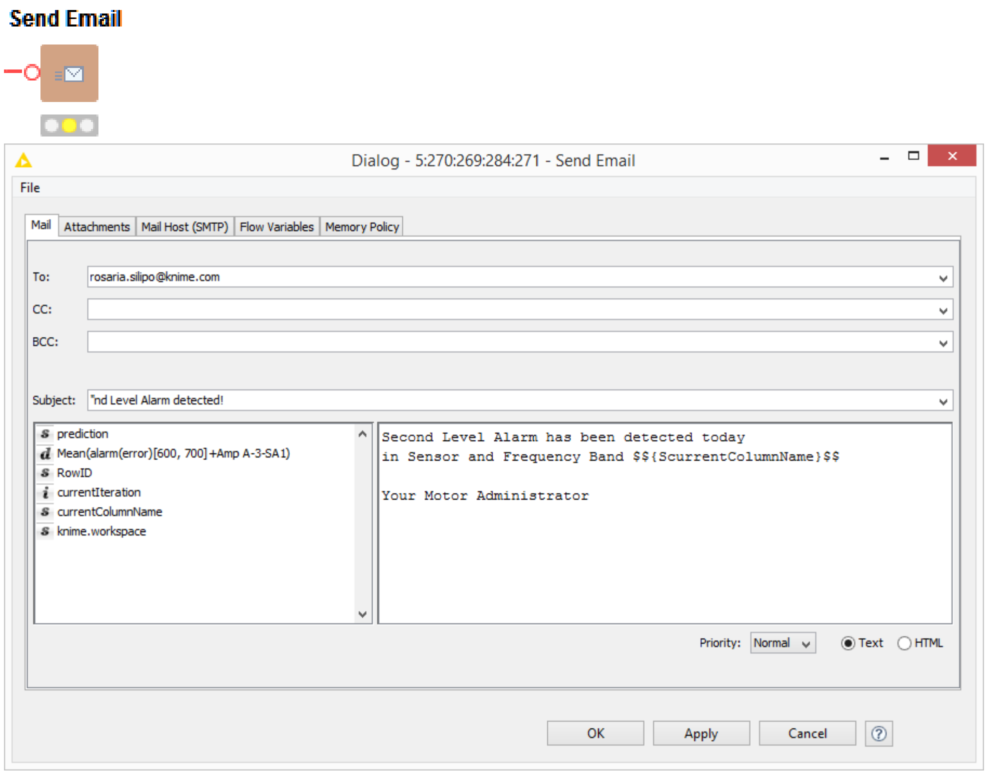
Greater than threshold ?



Anomaly Detection: Deployment of Second Level Alarm



Anomaly Detection: Deployment Triggers



via REST

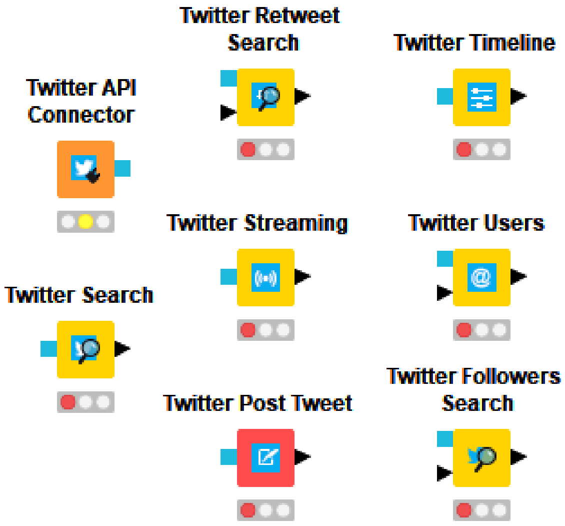
Lesson Learned

- Do women have less credibility as data scientist?
- When they see how good I am …

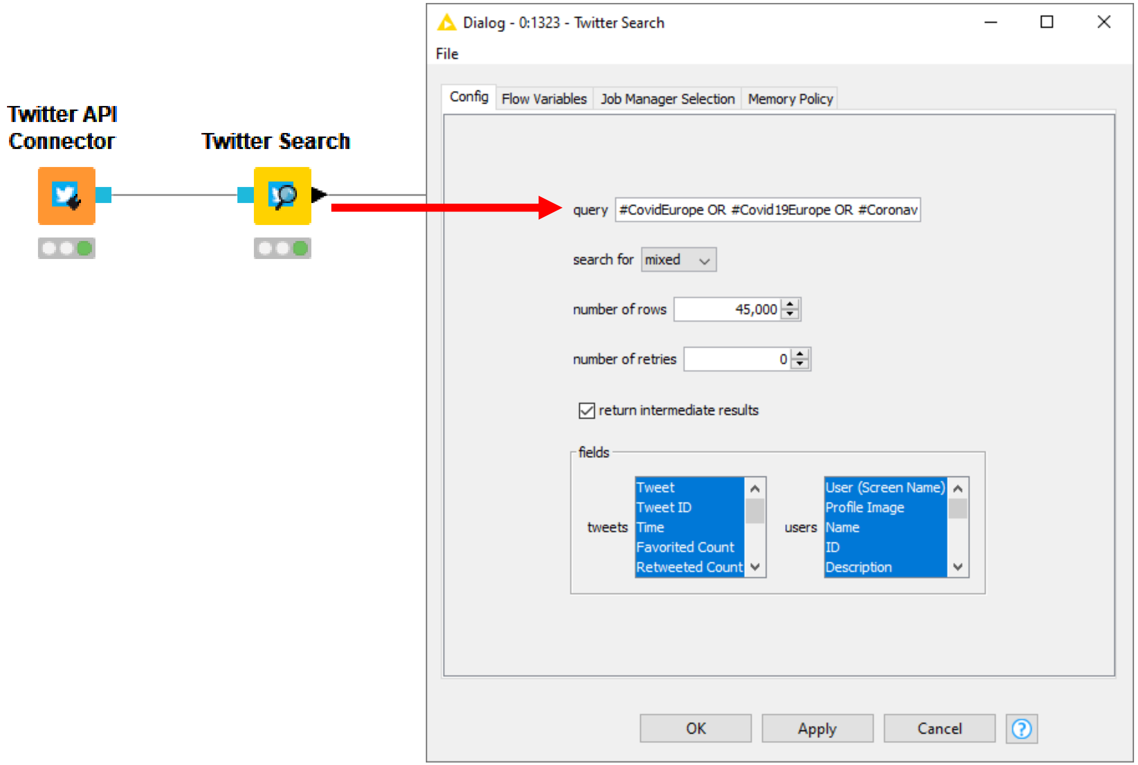
Mining Social Media Activity from Twitter

The Twitter API Integration

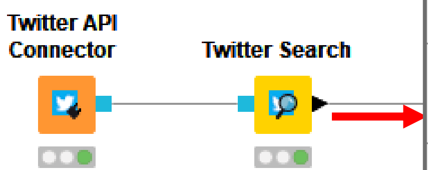
- To import tweets data directly into KNIME via official [Twitter API]
- Different nodes for different [tasks]
- Twitter API Connectors needs keys from a [Twitter app]



Use Case: Download #COVID19Europe Tweets

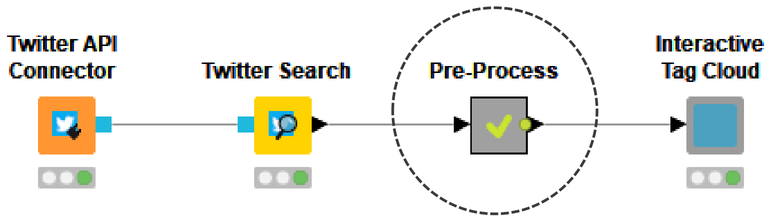


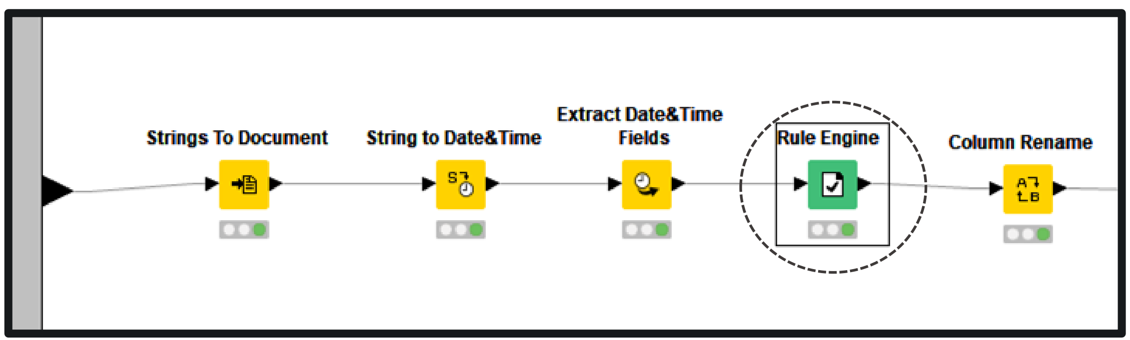
Use Case: Download #COVID19Europe Tweets

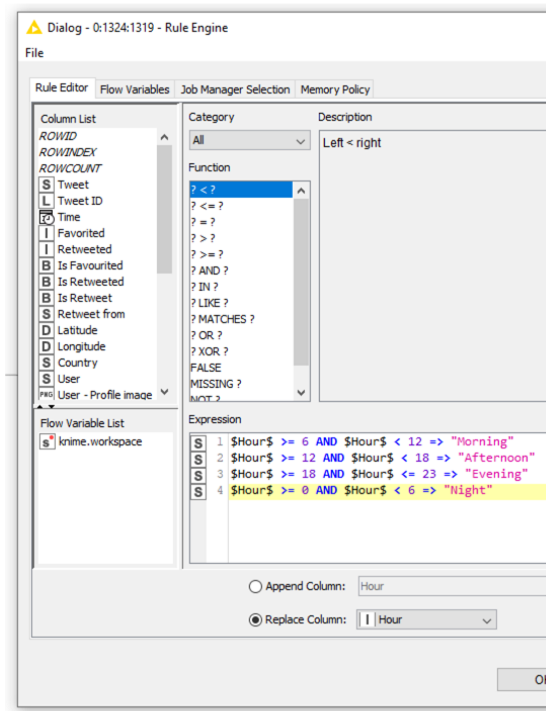


User - ...	User	Tweet	Tweet ID	Time
	Slabodkin	#COVID19 drives #EC to change rules on #notifiedbody designations https://t.co/E4xIy1zeBX #n...	1263141884643495...	2020-05-20 18:17:47
	mykonostick...	Οι χώρες της Ευρωπαϊκής Ένωσης πρέπει τώρα να επικεντρωθούν στις επενδύσεις στη δημόσια υγ...	1263096288985395...	2020-05-20 15:16:37
	riikka_kevo	Tässä koko pöytäkirja ko. kokouksesta. Tarkkuudella: kuka jäsenistä sanoi ja kommentoi mitä Euro... https://t.co/IsdEEmt9Kx	1263060976284336...	2020-05-20 12:56:17
	ernesturtasun	RT @RasmusAndresen: Happy to discuss the #covid crisis, the situation in Spain and a common eu...	1262808131127717...	2020-05-19 20:11:34
	RasmusAndr...	Happy to discuss the #covid crisis, the situation in Spain and a common european answer with my ...	1262805031851614...	2020-05-19 19:59:16
	Manos81A	Γίνονται και θαύματα? Ανάγκα και Γερμανοί πείθονται. Μην τους ματιάσουμε. #κορωνοιος #κορονοιος #covid19EUROPE #coronavirusEurope #COVID19Pandemic #Greece #c...	1262747384871714...	2020-05-19 16:10:11
	StokNathalie	150.138 #Corona Tote in #Europa - Stand 7. Mai Europa ist der von der #CoronaPandemie am härtesten getroffene Kontinent: Vor allem #Italien... #SARSCoV2 #ChinaVirus #CoronavirusDE #coronavirus	1262705115682742...	2020-05-19 13:22:14
	Aravalipoesia	RT @GAIA_Insights: The Language of Impactful Leaders, Join our next GAIA Gives free webinar o... Register here: https://t.co/yClMjG4esq #gaiainsights #together #webinar #resources #COVID19Europe #leadership https://t.co/xsr5OF...	1262676274943795...	2020-05-19 11:27:37

Use Case: Download #COVID19Europe Tweets

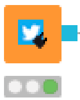






Use Cas

Twitter API Connector



Sentiment Analysis of Social Media Activity

Sentiment Analysis – An Example

Samsung

Samsung Galaxy S7 Edge G935A 32GB Unlocked - Gold Platinum

125 customer reviews | 606 answered questions

Beautiful phone from a wonderful seller!

By on May 29, 2017

Color: Gold | Verified Purchase

This practically new beautiful phone well exceeded my expectations!

One Star

By on August 3, 2016

Color: Black Onyx | Verified Purchase

Very bad experience

Sentiment Analysis – Some Use Cases

- ***Movies***: is this review positive or negative?
- ***Products***: what do people think about a new smartphone?
- ***Politics***: what do people think about a specific candidate or political issue?
- ***Prediction***: predict election outcomes or market trends from sentiment.

Today's Use Case

- Dataset: subset of the IMDb (Internet Movie Database) Large Movie Review Dataset v1.0 with 2000 documents(*).
  - 1000 documents from the positive group
  - 1000 documents from the negative group

- Goal: To assign the correct sentiment label to each document.

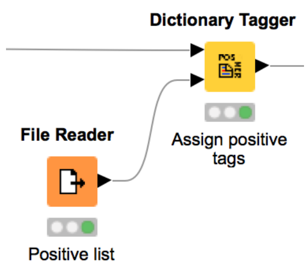
(*) For details about the data set see http://ai.stanford.edu/~amaas/data/sentiment/
Data citation: Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. (2011). Learning Word Vectors for Sentiment Analysis. The 49th Annual Meeting of the Association for Computational Linguistics (ACL 2011)

Sentiment Analysis

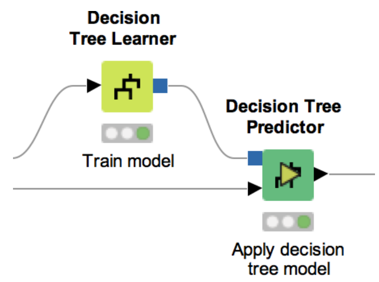
Task: Determine the expressed opinion in a document/text, e.g. positive, negative

Sentiment Analysis = Opinion Mining = Emotion AI

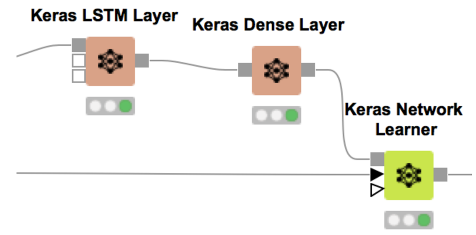
Lexicon Based



Machine Learning



Deep Learning



Approach 1: Lexicon Based

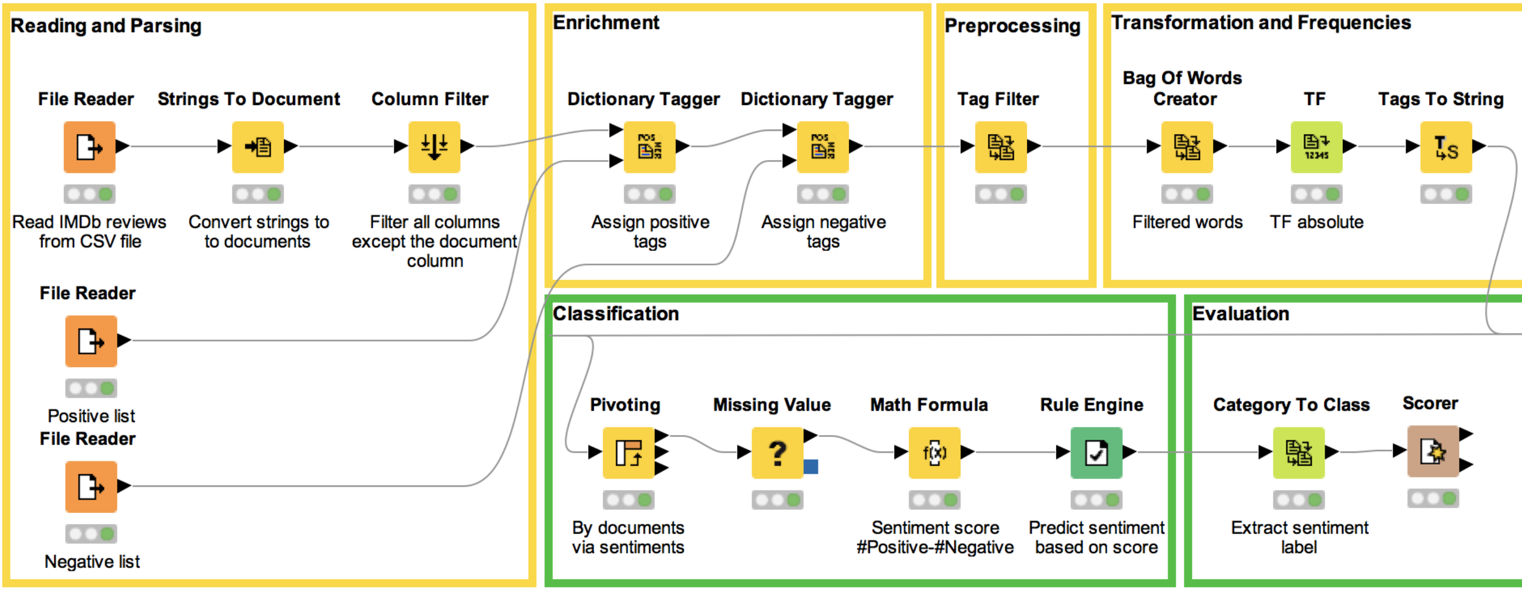
Idea: Rule-based classification with Dictionary Tagger

1. Use custom dictionary to tag positive and negative words
2. Count number of positive and negative words per document
3. Assign classes depending on the number of positive and negative words

$$sentiment\ score = \frac{\#\ positive\ words - \#\ negative\ words}{\#total\ words}$$

Advantage: No labels needed

Rule-based Classification with Dictionary Tagger



Approach 2: Machine Learning

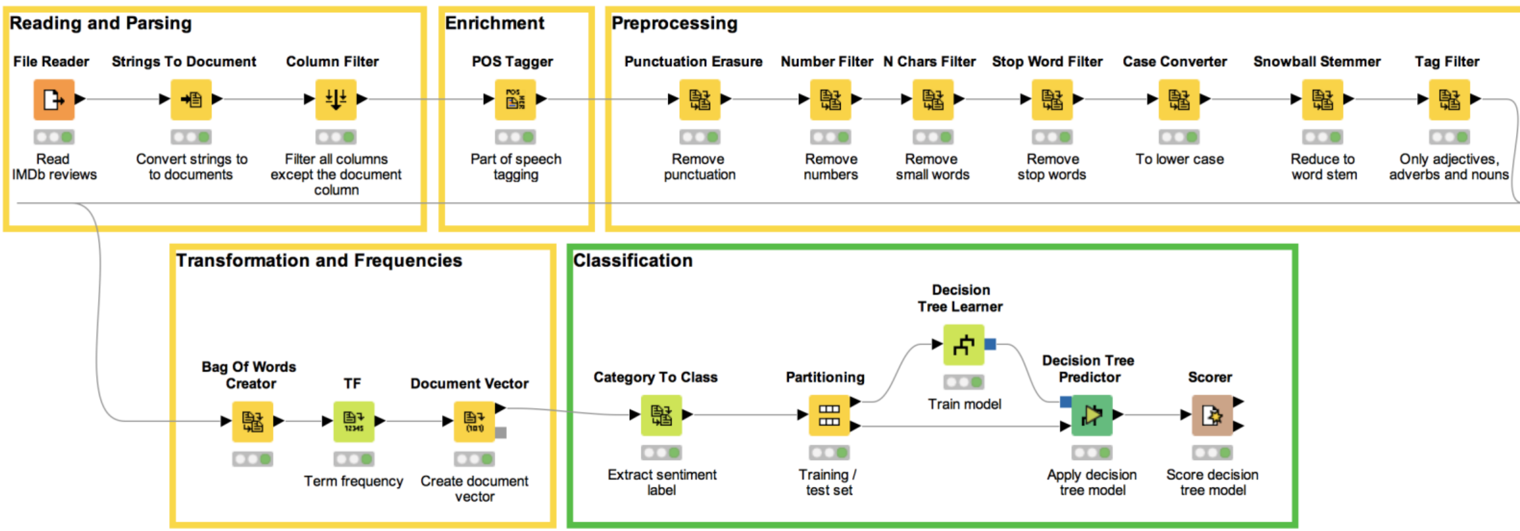
Idea: Train a model to make predictions on unseen data

1. Start the analysis with a labeled dataset
2. Extract a feature space from the documents, e.g. only keywords
3. Train a supervised model, e.g. decision tree, logistic regression

Advantage: Better performance

Vohra, S. M., and J. B. Teraiya. "A comparative study of sentiment analysis techniques." Journal JIKRCE 2.2 (2013): 313-317.

Approach 2: Machine Learning



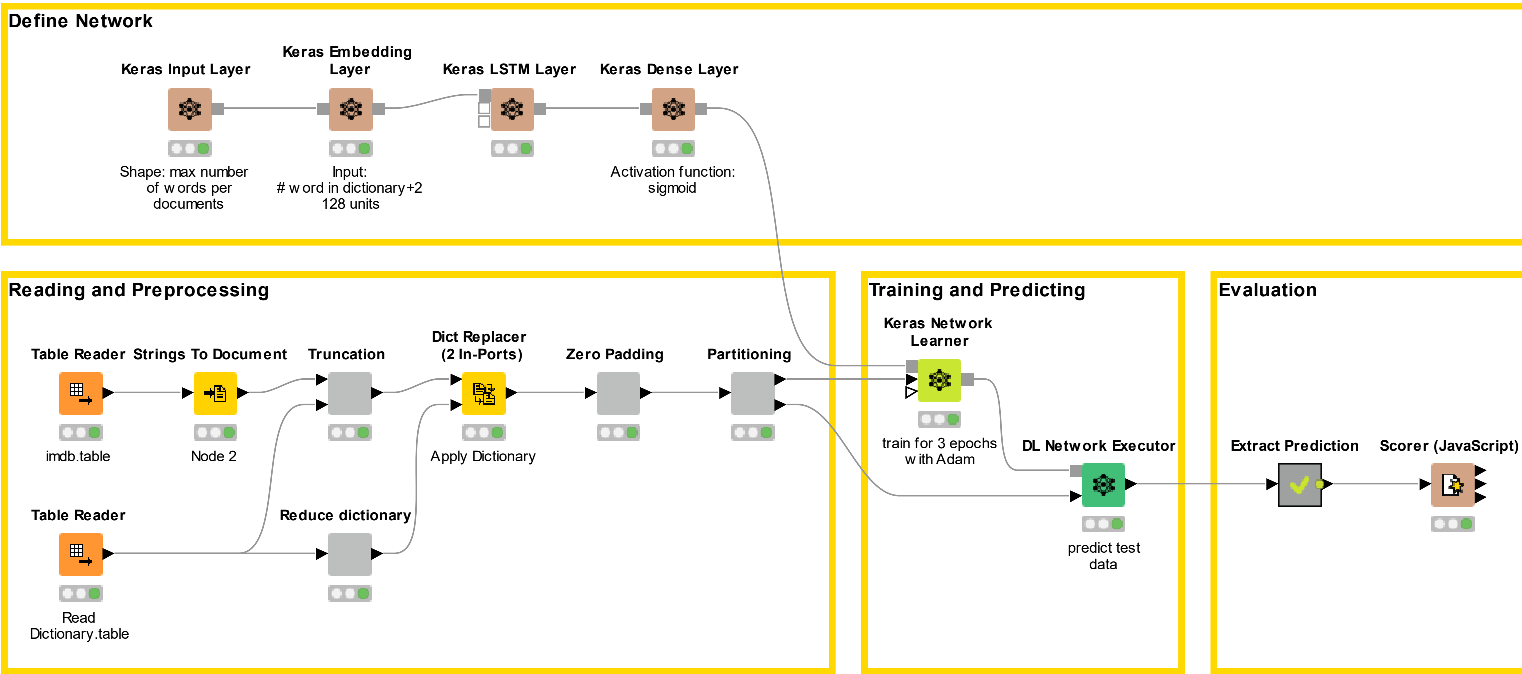
Approach 3: Deep Learning

Idea: Train a network to make predictions on unseen data

1. Start the analysis with a labeled dataset
2. Bring the documents into a standard numeric shape
   - Hot encoding vs. embeddings
   - Zero padding and truncation
3. Define the network structure. Commonly used layers for text are embedding and LSTM layers
4. Train and apply the network

Advantage: Can lead to better performance on big data sets

Approach 3: Deep Learning



Topic Detection in Documents with LDA

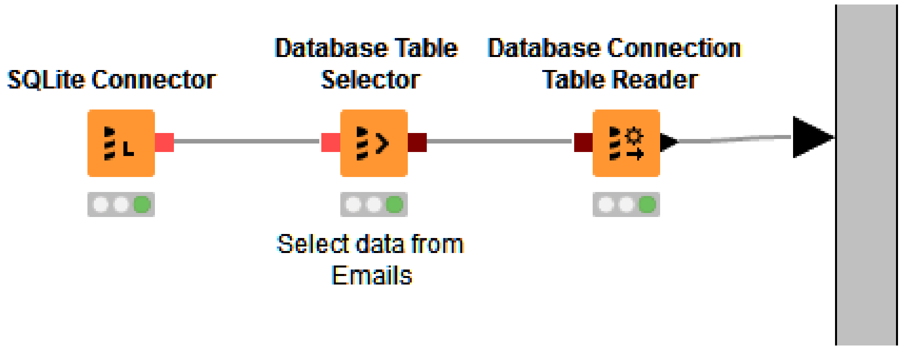
Background Story

- Controversy regarding former Secretary Hillary Clinton’s use of a non-government, privately maintained email server
- On 2015, Hillary Clinton released 7,945 emails in response to a U.S. Department of State Freedom of Information Act (FOIA) request
- The original emails are available on the State Department’s Website

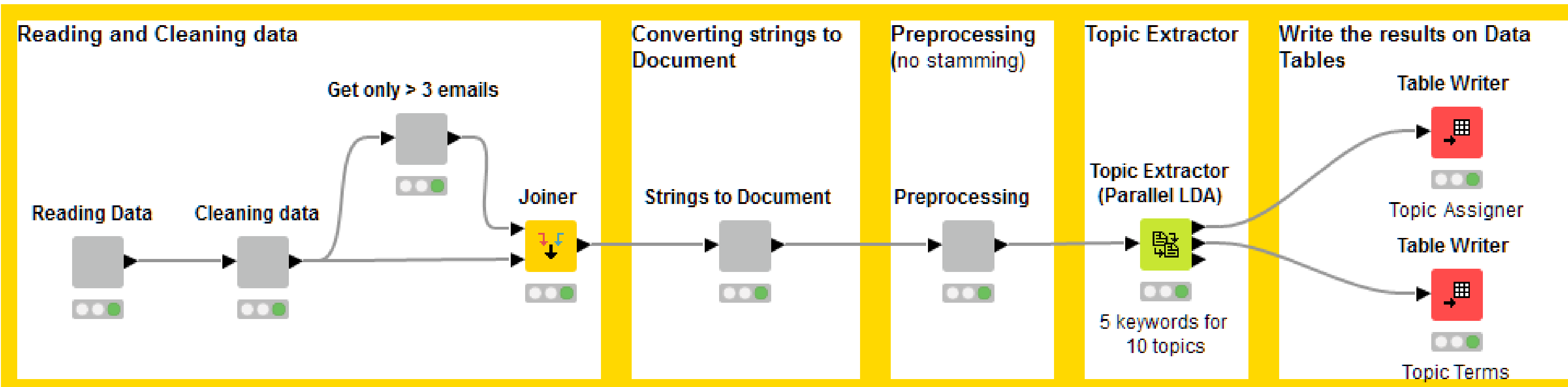
Acquiring and Accessing the Data

- Data available at
  kaggle.com/kaggle/hillary-clinton-emails

- The data have been downloaded and accessed as SQLite database

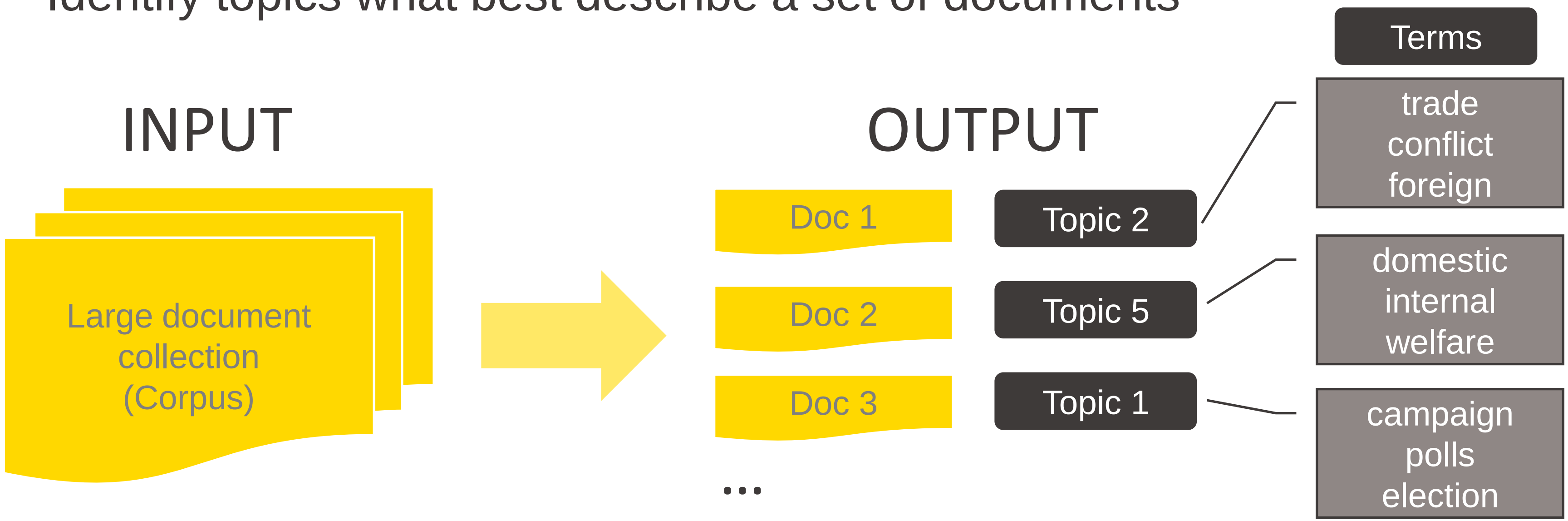


Training Model



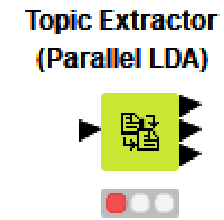
What is Topic Modeling?

- Developed to organize large collections of documents and to **extract the hidden thematic structure**
- Identify topics what best describe a set of documents



Latent Dirichlet Allocation (LDA)

- Automatically finds the top K topics with the most relevant N keywords discussed in a collection of unlabeled documents (considered unsupervised)
- It represents documents as random mixtures over latent topics, where each topic is characterized by a distribution over words
- Syntax or order of the words in document is not important (bag of words model)
- Document order is not important
- The same word can belong to different topics
- **The number of topics needs to be selected/known in advance**

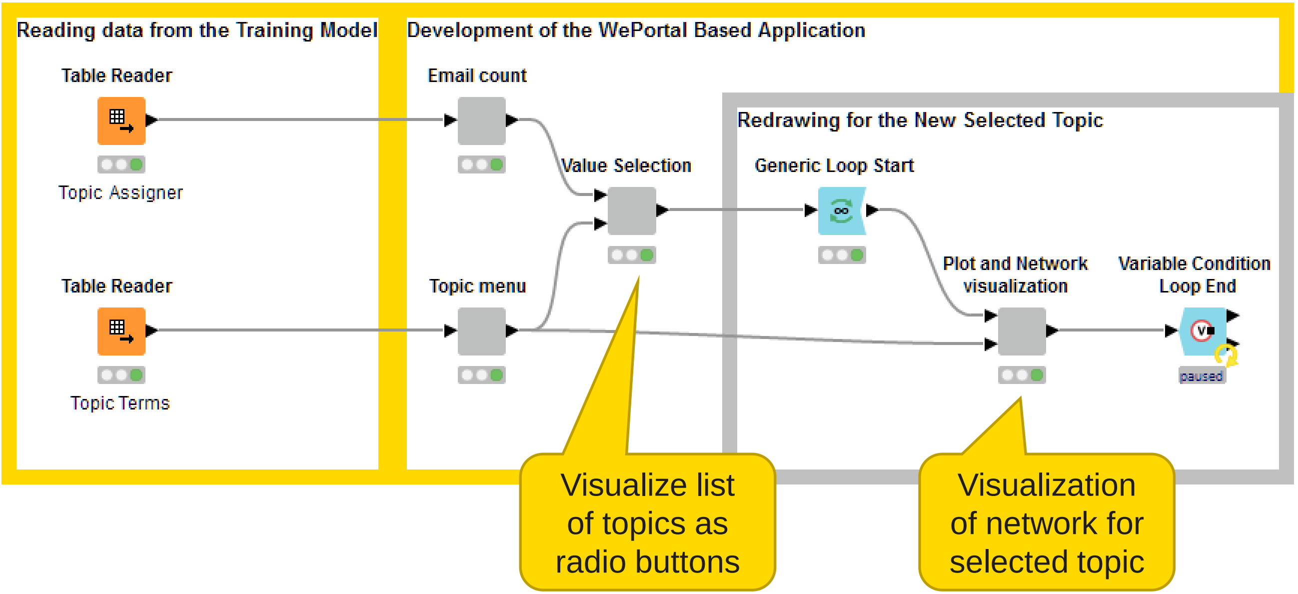


Blei, David M., Andrew Y. Ng, and Michael I. Jordan. 2003. **"Latent Dirichlet Allocation."** *Journal of Machine Learning Research* 3: 993–1022.

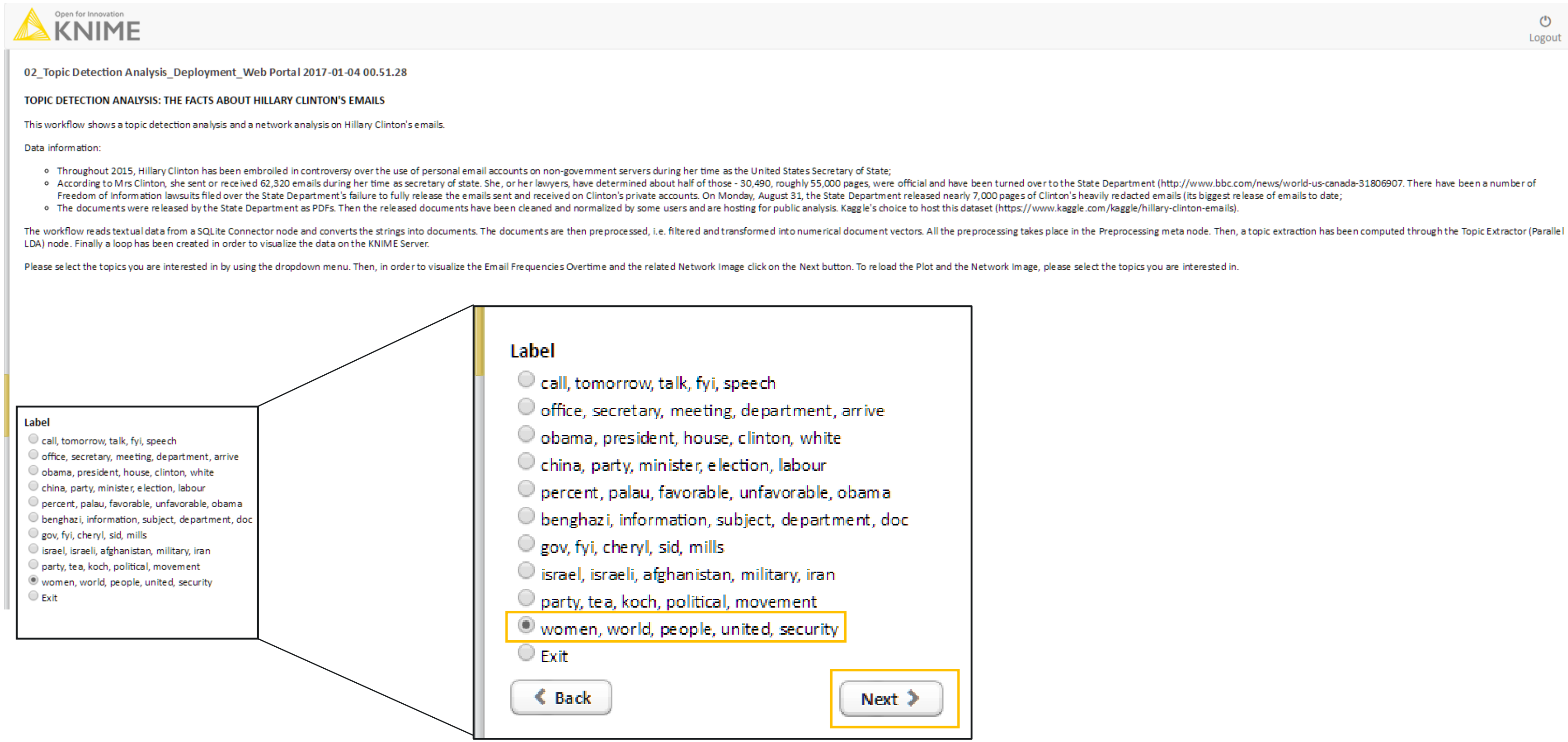
Results: Topic and Terms

Topic id	Term
topic_0	[call, tomorrow, talk, fyi, speech]
topic_1	[office, secretary, meeting, department, arrive]
topic_2	[obama, president, house, clinton, white]
topic_3	[china, party, minister, election, labour]
topic_4	[percent, palau, favorable, unfavorable, obama]
topic_5	[benghazi, information, subject, department, doc]
topic_6	[gov, fyi, cheryl, sid, mills]
topic_7	[israel, israeli, afghanistan, military, iran]
topic_8	[party, tea, koch, political, movement]
topic_9	[women, world, people, united, security]

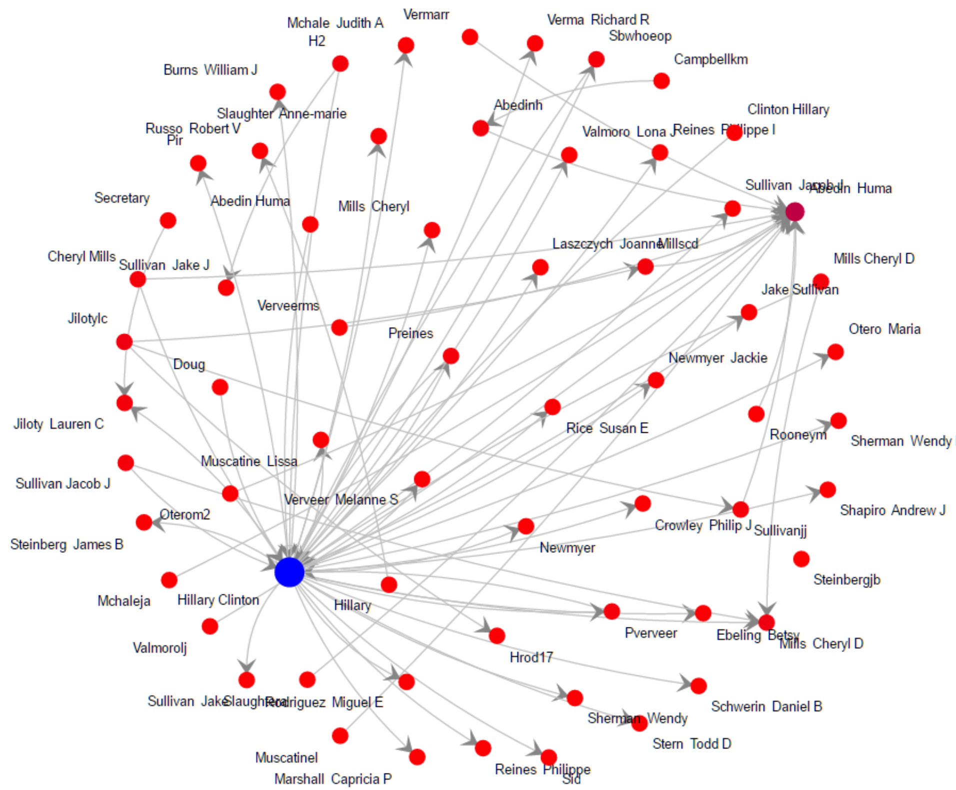
Deployment Model



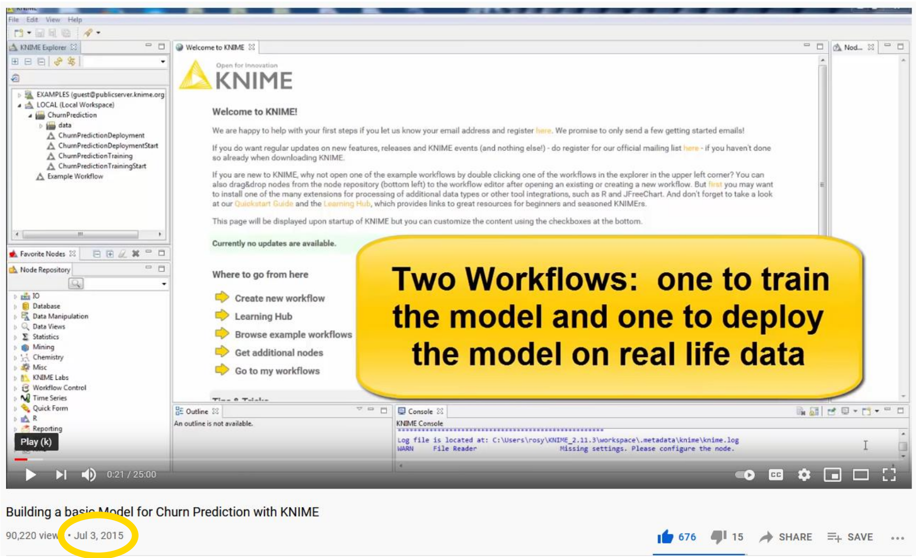
WebPortal – First Webpage

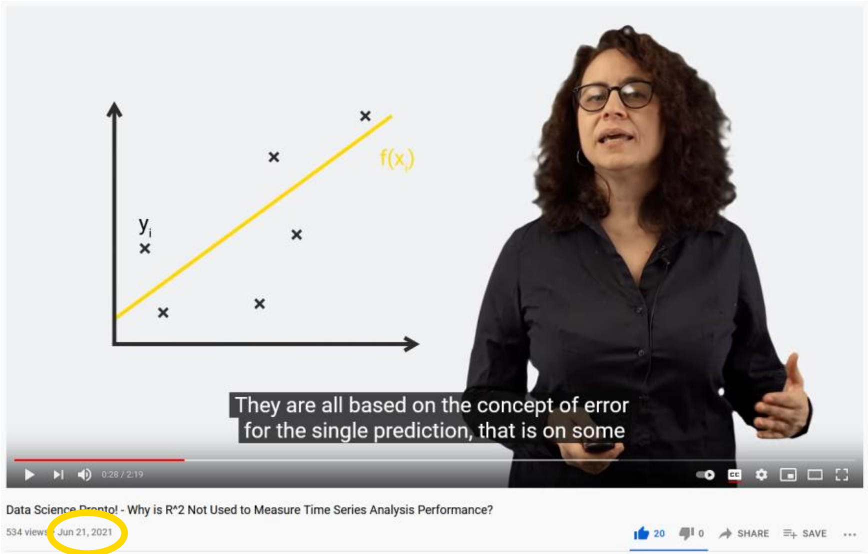


Women, World, People, United, Security



Lesson Learned





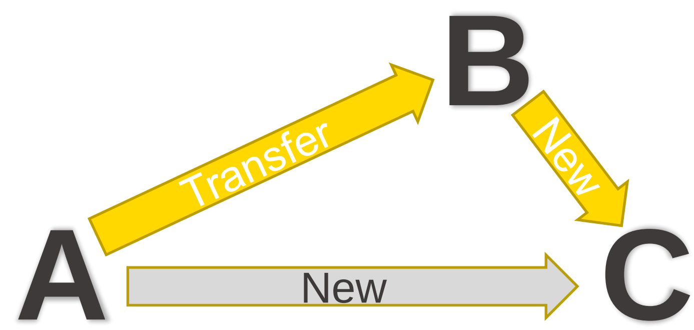
- Do not wait till everything is perfect to start …

Cancer Cell Classification

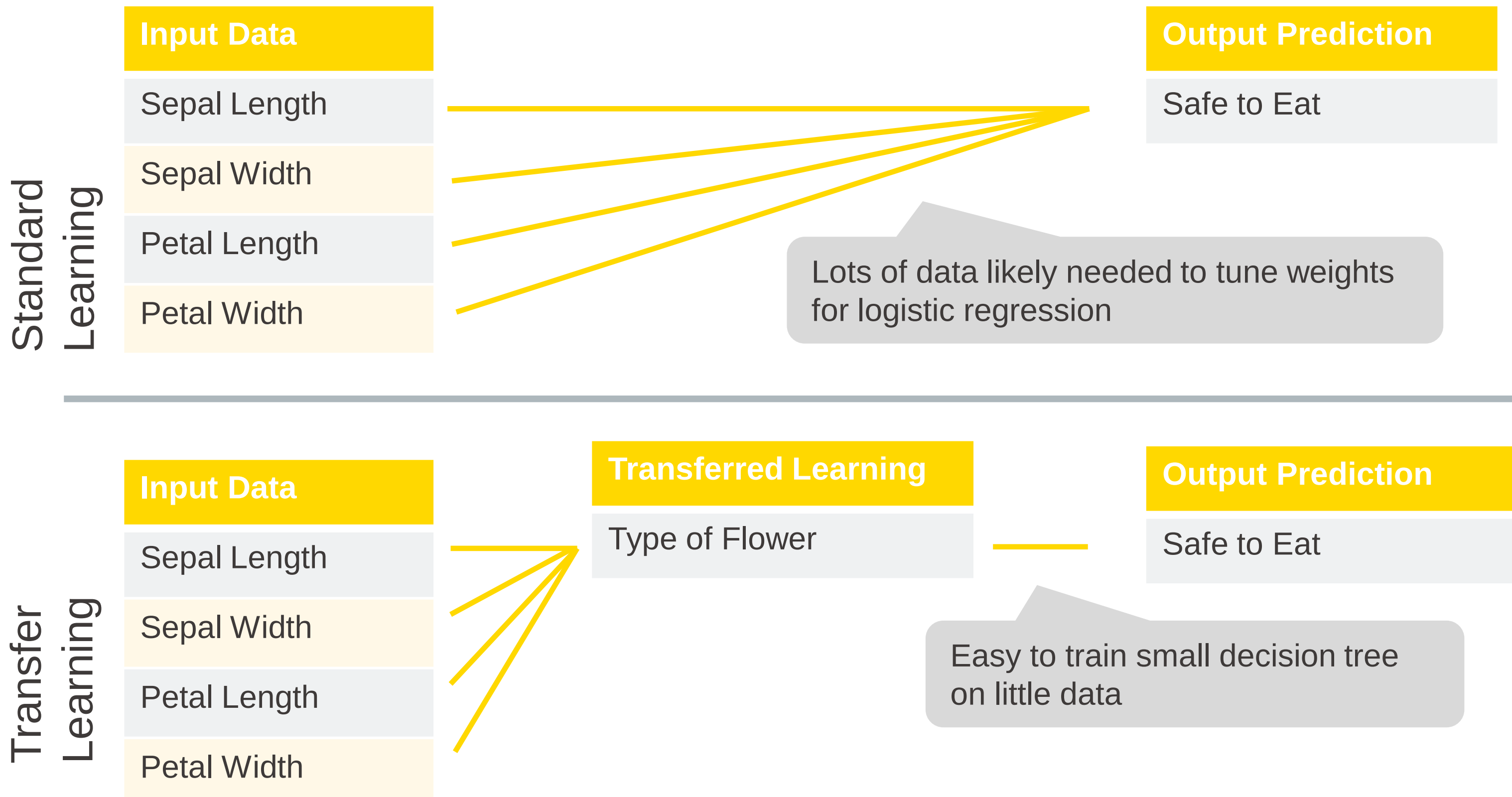
What is Transfer Learning?

- Transfer learning can be defined as the attempt to utilize predictive ability in one input / output space to aid in the learning of new input spaces, output spaces, or both.

- In this use case the input space, 3x64x64, remains the same, but the output space changes from 1000 image categories to 3 cancer types.



Transfer Learning – Basic Example



Cancer Cell Classification Use Case

- Uses Keras Deep Learning model.
- Learning *Transferred* from VGG16 image classifier
- Completely code free with KNIME's Deep Learning Integration
- Can be adapted to a wide range of image classification problems

Original Task

This Photo by Unknown Author is licensed under CC BY-SA

VGG16 → Cat

New Task

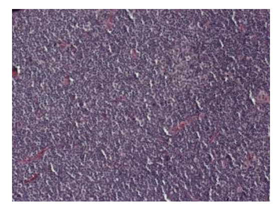
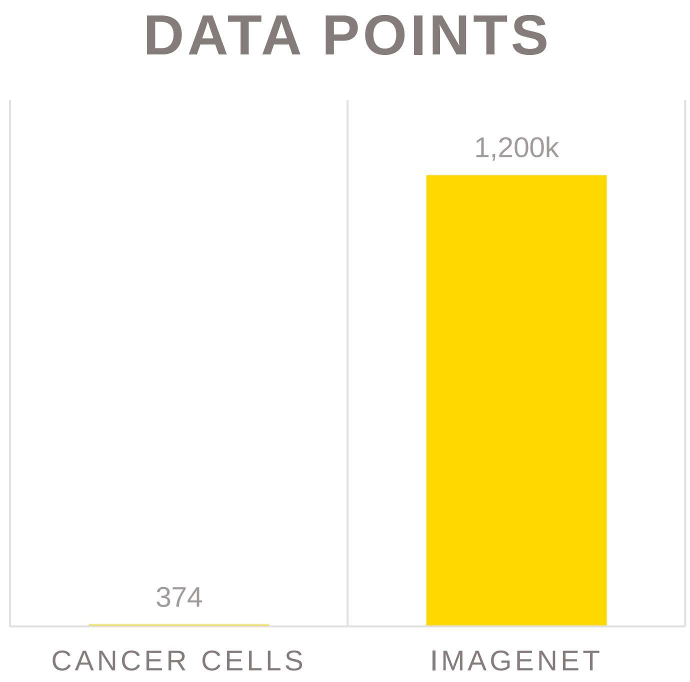


Image From: https://ome.grc.nia.nih.gov/iicbu2008/lymphoma/index.html

VGG16 → New → CLL

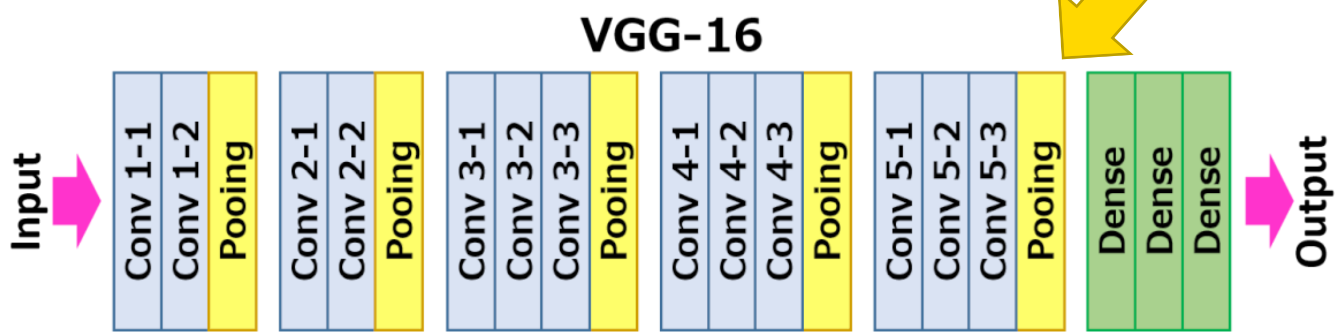
Why is it helpful?

- Deep Learning requires tons of data
- Image classification requires tons and tons of data
- We have 374 labeled cancer images
- VGG16 was trained on more than 1,000,000 images from ImageNet dataset.



VGG16 Model

Final Layer
We used

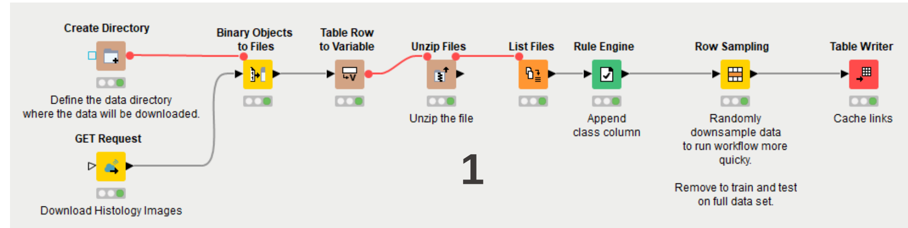


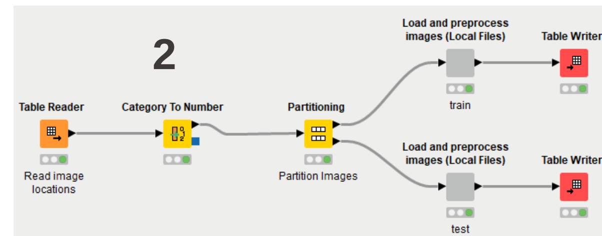
VGG16 Architecture: https://neurohive.io/en/popular-networks/vgg16/

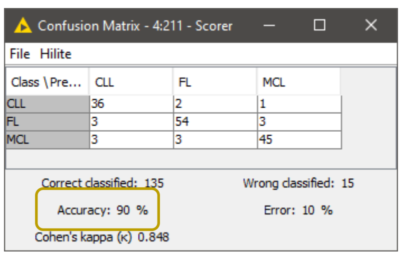
- Several blocks of small convolution layers followed by max pooling layers
- Trained on **ImageNet** dataset
  - Over 1,000,000 images from 1,000 thousand classes
- Won ILSVRC-2013 competition in single network category

Everything in KNIME

1. Download Data Set
2. Pre-Process Data Set
   - Crop, Normalize, Rearrange
3. Configure Network
   - Load VGG16
   - Add and Freeze Layers
4. Train Network
5. Post-Process Predictions
   - Group images, create Classification






Confusion Matrix - 4:211 - Scorer

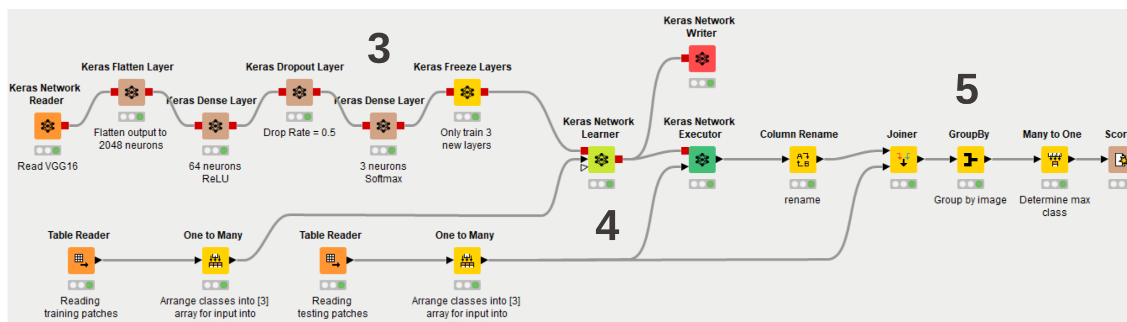
File Hilite

Class \ Pre...	CLL	FL	MCL
CLL	36	2	1
FL	3	54	3
MCL	3	3	45

Correct classified: 135 Wrong classified: 15

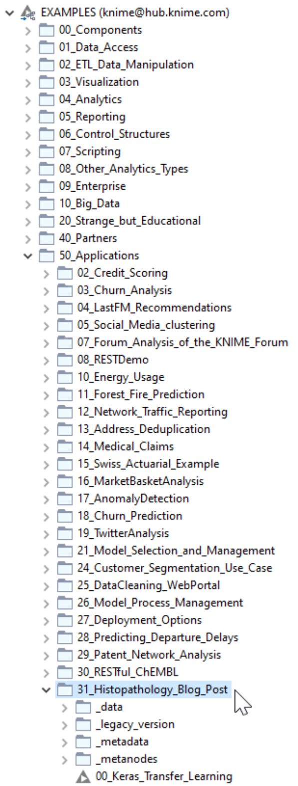
Accuracy: 90 % Error: 10 %

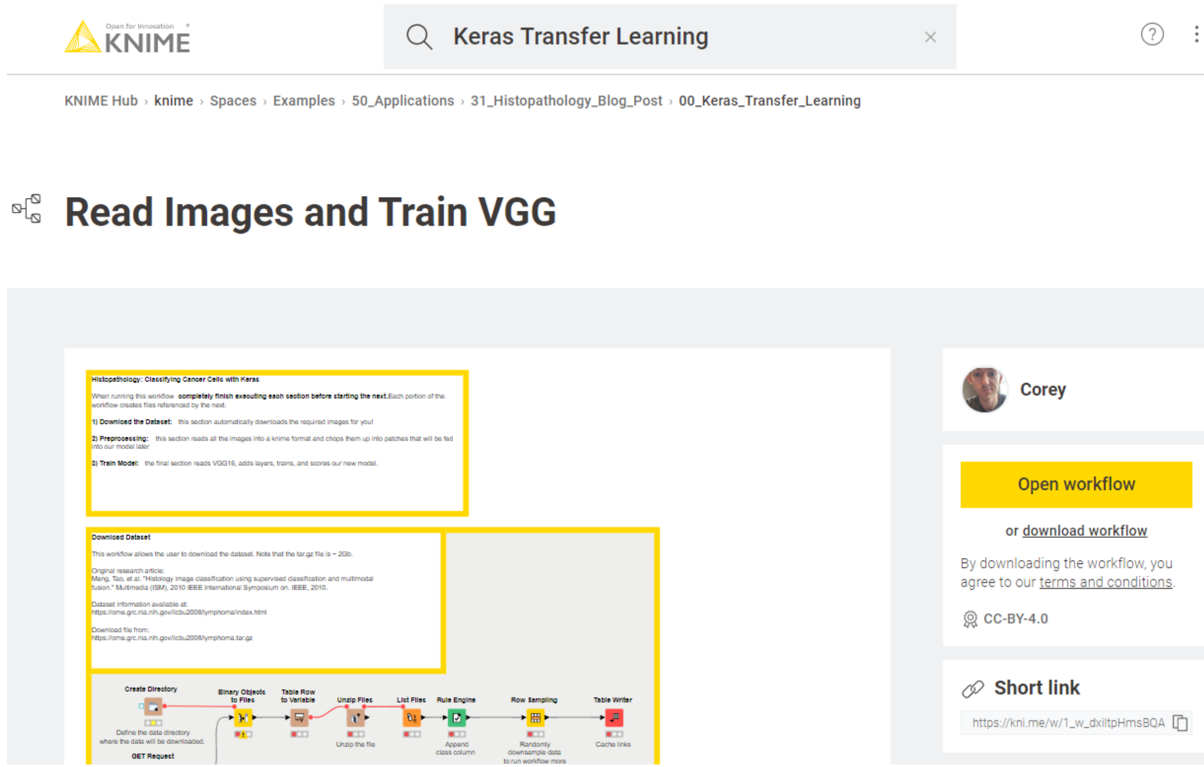
Cohen's kappa (κ) 0.848



Workflow on KNIME Hub:
https://kni.me/w/1_w_dxiltpHmsBQA

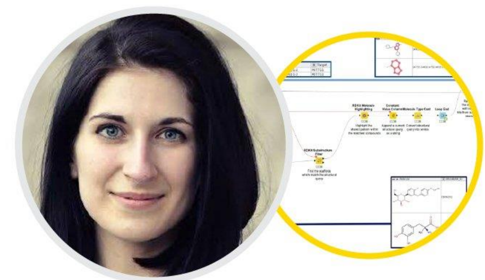
Finding the Example





Lesson Learned

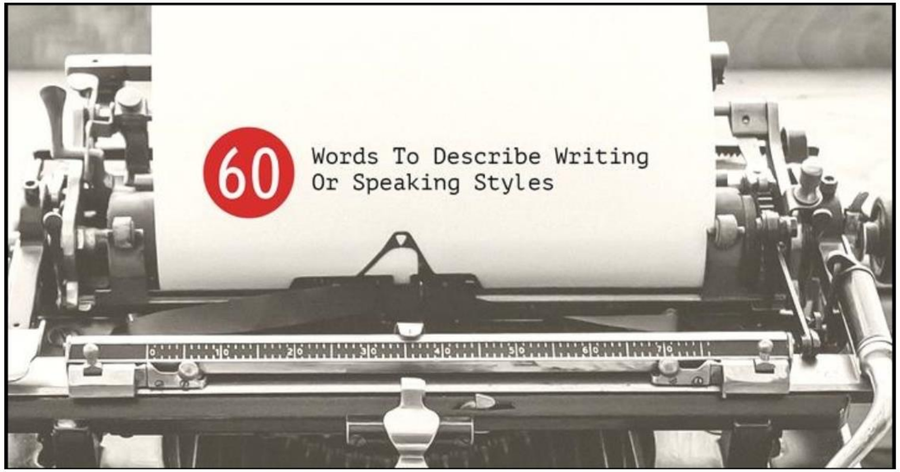
- Do we need more women in Data Science?
- Is the emergency over?



Creative AI: Free Text Generation

Bots & speaking styles

- Articulate
- Chatty
- Clean
- Conversational
- Crisp
- Declamatory
- Diffuse
- Discoursive
- Eloquent
- Emphatic
- Epigrammatic
- Epistolary
- Euphemistic
- Flowery
- Funny
- Fluent
- Formal



60 Words To Describe Writing Or Speaking Styles

- Gossipy
- Idiomatic
- Incoherent
- Informal
- Journalistic
- Literary
- Lyric
- Ornate
- Parenthetical
- Pejorative
- Picturesque
- Poetic
- Prolix
- Punchy
- Rambling
- Rhetorical
- Rough
- Sesquipedalian

https://writerswrite.co.za/60-words-used-to-describe-writing-or-speech-style/

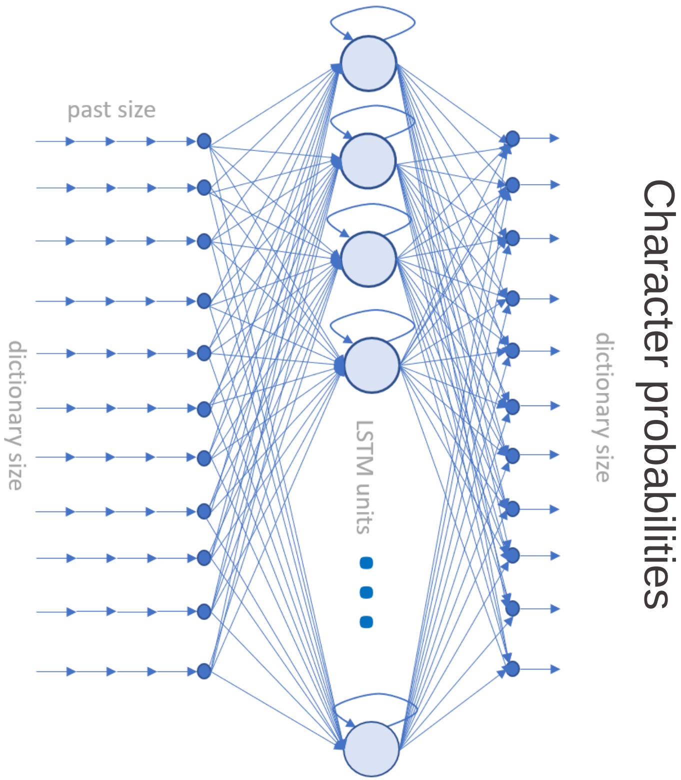
Creative AI: The Problems

- Free Text Generation
  - Simulating a writing style
  - Writing in different languages
  - Providing an answer in a specific style
  - Generating candidates for product names

Deep Learning LSTM Network

e - s- u – o - h

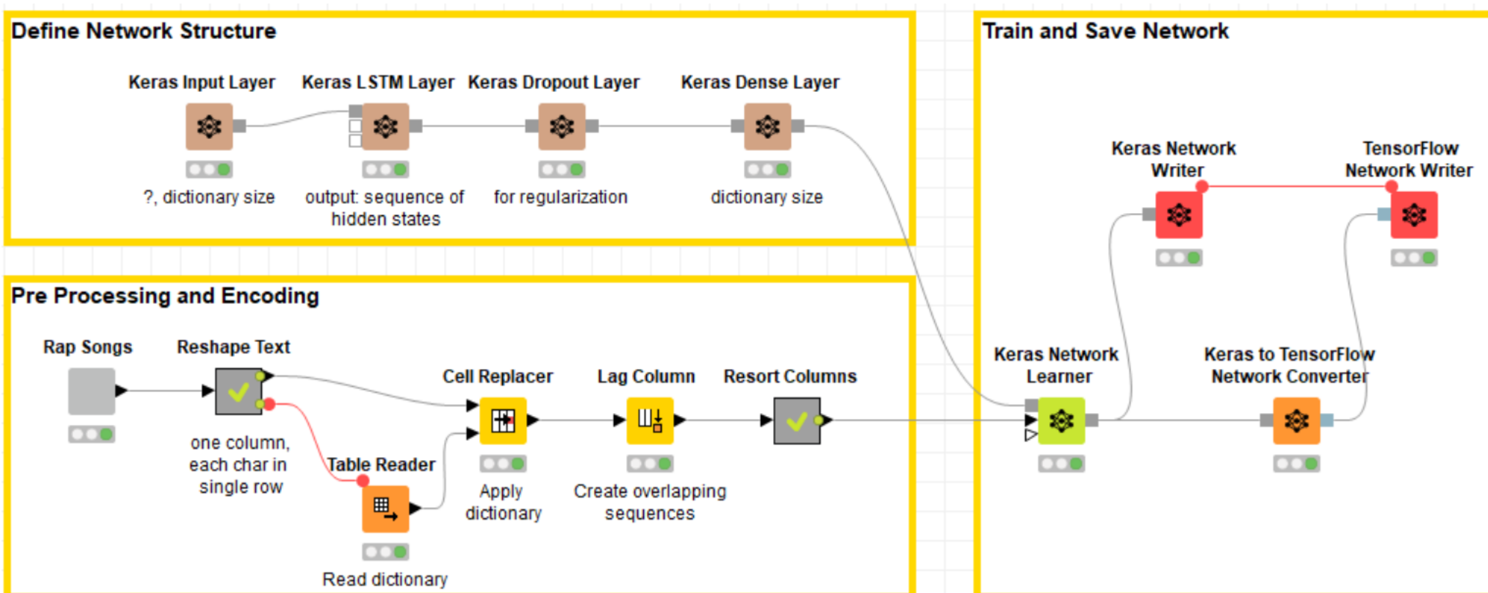
One-hot encoded character



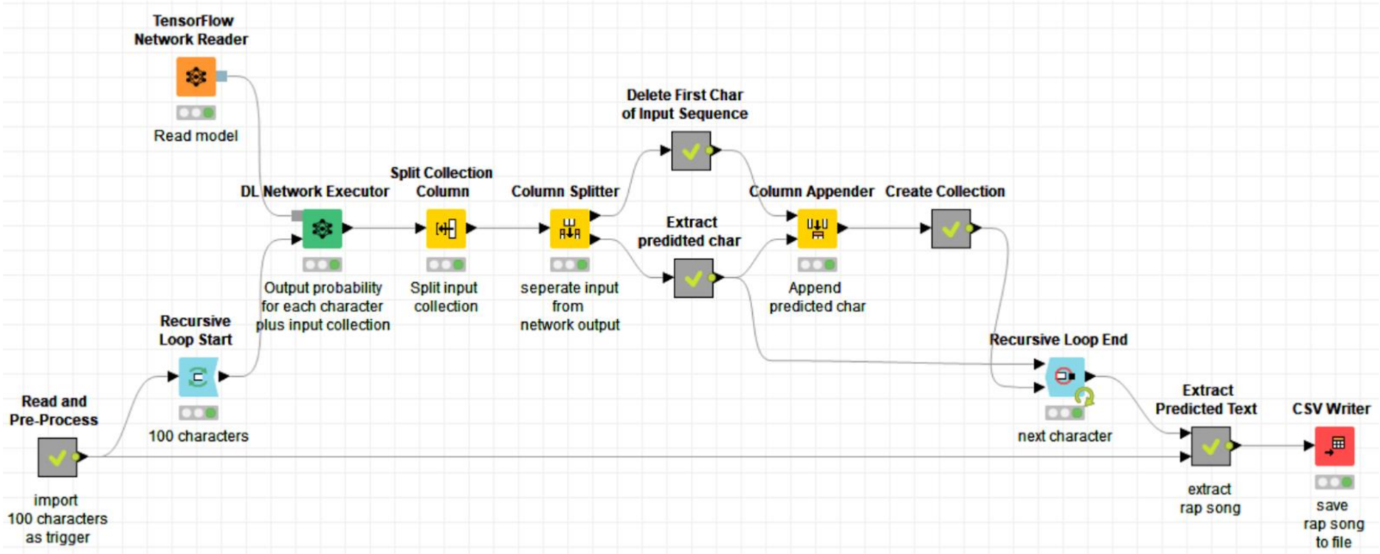
Character probabilities

o - u- s - e - <space>

Creative AI: The Training Workflow

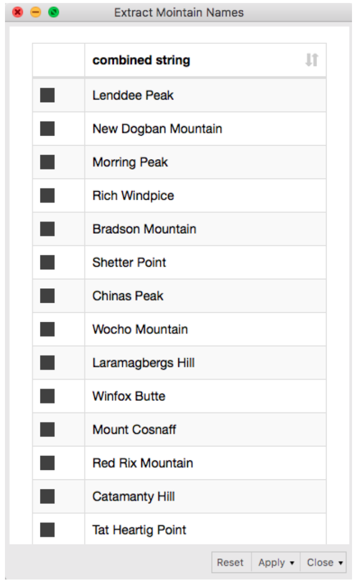


Creative AI: The Deployment Workflow



Creative AI: Deployment and Results

*Yo! This post is about generating free text with a deep learning networked the word
then I think they don't wanna be the land
This that I could take your b**** a** n****
off you in the street
or make you were been would 'cause
the pigtod on my s***,
what my trues I need you right in back in a burble
It ask me, I can see the winds I swear these n*****
a** since when I'm not cool on my for it when
I see you n***** that I'm all the one tryna tell me
you hot the done of the last this is no other can't expersive,
then I got my whip
When I get my drow bood and my street with some b****
and the plan is a clear out all my pass that bullshit
When I get my dronk If I got my money right
it's still the same I'm so high
Me and do your hands in the almed and I'm fresher
I'm a bad b***
I'm a body in her friend on my whip
You ain't with the world the weard
and then he give me a n**** dough?
And my car is with the bunch of life of the drummers
and a crannead and ride with my baby I just lang
Mire thes as to see your friend like a m**********' shade
and started when I came the box I just had to live in a cokin'
up in that b****** (b*******)
You ain't cheap (yeah)
Then we feelin' like the president (the phine, watch)
If you get shotts (Ahooh)
I kick the right things If I said,
I get the streets still gon' shoot me so cold weave and make me wanna show me at the top of the back are
I want to get me here
I can see you a mastac (lean, fuck me fersin')
I don't even cold Ten (bottom)
I know I gotta keep my shere in a migat (Woo, woo,*



*This License refers to version of the GNU General Public License.
Copyright also means copyright-bick,
Remade me any thing to his sword
To his salt and most hidden loose to be so for sings, but not in a libutt of his matter than that shall be sure as will be soldye
As master company, do not live in traitor.
Bless thy five wits!*

-Kent
*O pity!
Sir, where is the patience now,
That this is so far from the sea and some bidings to dismantle
So many folds of save and honest.*

-Brabantio
*I must not think the Turk of Cassio in the strange metting the cribles of a charmer be the reviling of libe to say
That I can deceive him to the best advantage,
In her prophetic fairs of a little to presently at your powers; whereof I thank you, sir.*

-Albany
Gloucester, I will prove upancy of his sport and first accuriors and guard and talking on the white.

-King Lear
*Where are the thief?
Thou shalt never have the captains at the letter
To the Moor and thing we have not the better shall be sure as worth if he be anger—*

-Regan
I pray you, have a countend more than think to do a proclaim'd there of my heart, Hot

The words save, honest, thief, master, traitor, and deceive seem to fit the context. Notice also that the dialogue sprouting from the start text of the license agreement interestingly involves mainly minor, less tragic characters from the plays.

Caro amico ti scrivo così mi distraggo un po'E siccome sei molto lontano più forte ti scriverò. Da quella prima folla strana, che aveva preso il suo nome, e di correre alla casa di don Abbondio, con un viso bene di non poterci andar la casa del padre Cristoforo, e gli disse che s'avvicinava all'uscio, e si mise a sparse di corsa, e di stare a sé, verso la strada di servizio, chiesto le parole che gli andavan dall'altra stanza, e con la sua condizione de' cappuccini, e di consigli ricerche di confidenza delle gride, nel suo passaggio, se non pensava con una certa ripugnanza a casa sua, che andavano a scomparire in un campo di buone ragioni che avevan potuto raccogliere i suoi pensieri, e di sopra non senza interrogare, che la sua avventura aveva fatto predicare, e con la forza d'un fatto come fuggitive che aveva preso il suo nome, e di correre alla casa di don Abbondio, con un cappuccino di quella sorte, con un certo sospiro, alzando le sue finestre, e le diede un'occhiata in carrozza. Si vendano a metter nelle mani di chi era stato a sedere sur una strada così fatta con le braccia in

Open for Innovation KNIME

Creative AI: A Touch of Art in Thimble Images

Creative AI: The Problems

- Image Neuro-Styling
  - Picasso
  - Botero
  - Matisse
  - Manet
  - …

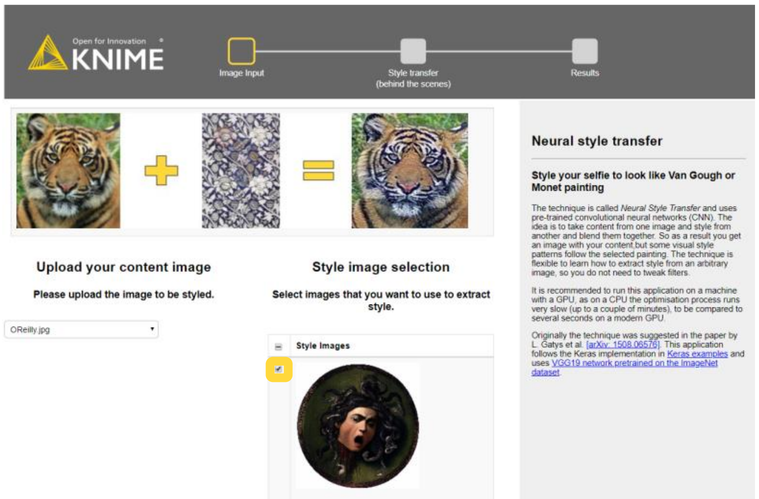


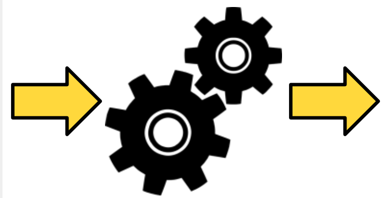







Image Neuro-Styling





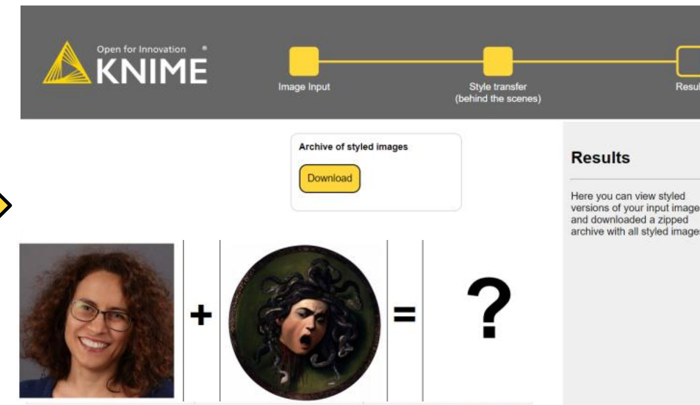
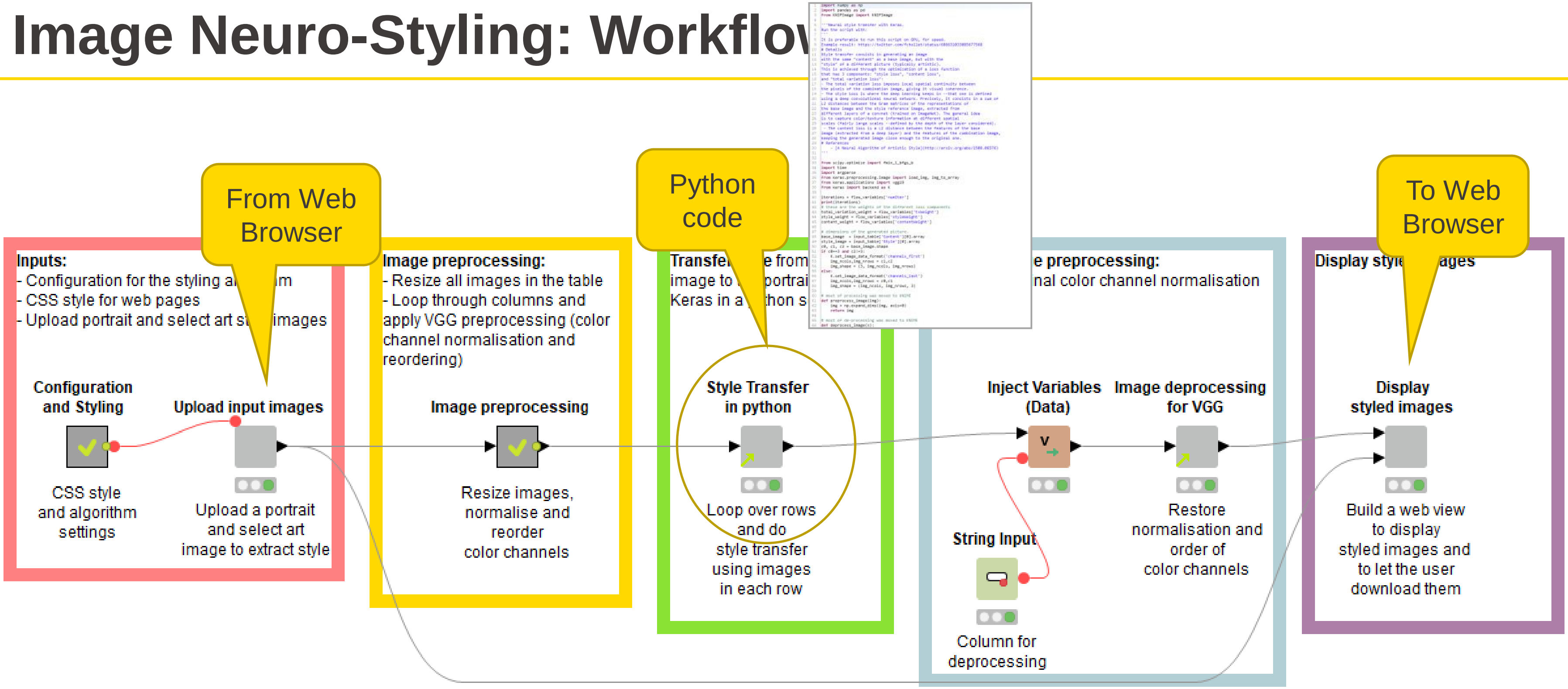


Image Neuro-Styling: Workflow



Note, the app requires Deep Learning and python extensions installed. Follow instructions relevant for the Keras extenstion installation in:
https://docs.knime.com/2018-12/deep_learning_installation_guide/index.html#keras-integration

Rosaria Neuro-Styling


original


Picasso


Magritte


Caravaggio


Notre Dame


Artemisia


Manet


Tapestry


Matisse

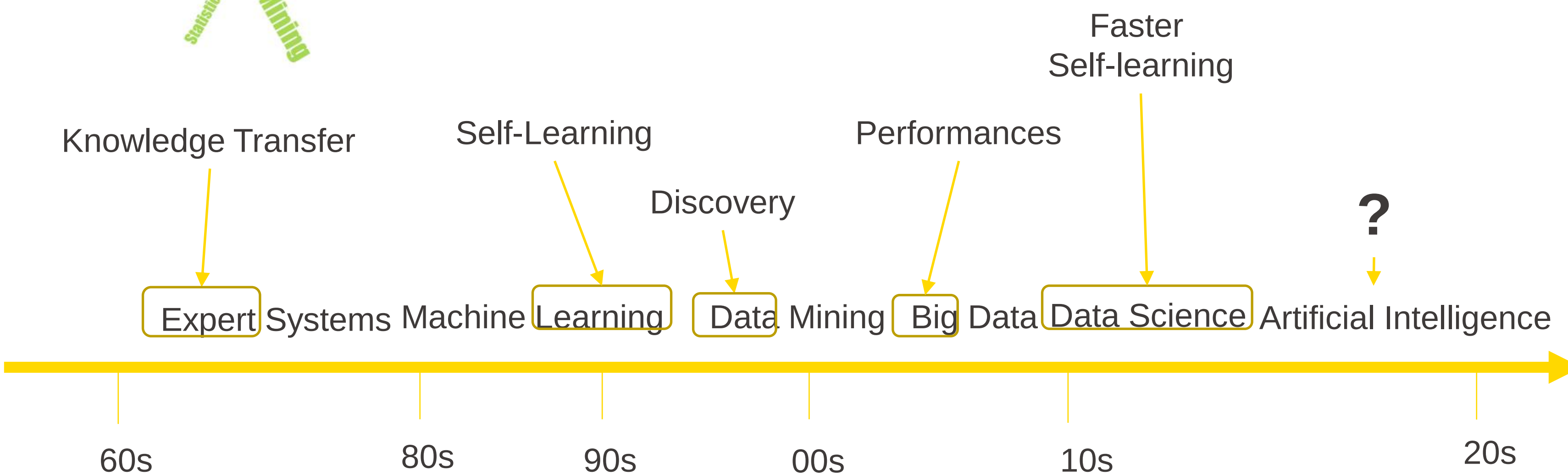

Renoir


Van Gogh


Botero

Lesson Learned

https://betanews.com/2019/02/05/artificial-intelligence-or-data-science/



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