Week 5: Industry Applications of Deep Learning

Unit 1: Machine Learning from an Application Point of View

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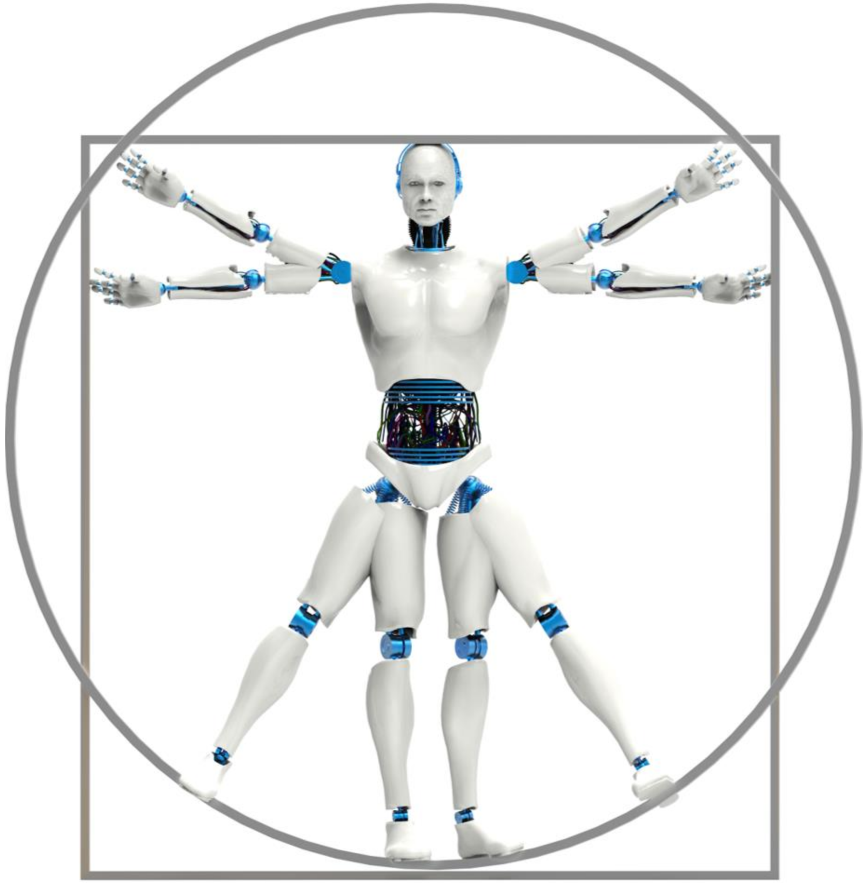
Machine Learning from an Application Point of View

Learning goals for this unit

- Which aspects from an application point of view are important to select valid machine learning use cases
- How to apply the Feasibility – Desirability – Viability approach to validate your ideas for machine learning products
- Which criteria you should check to make your go / no-go decision



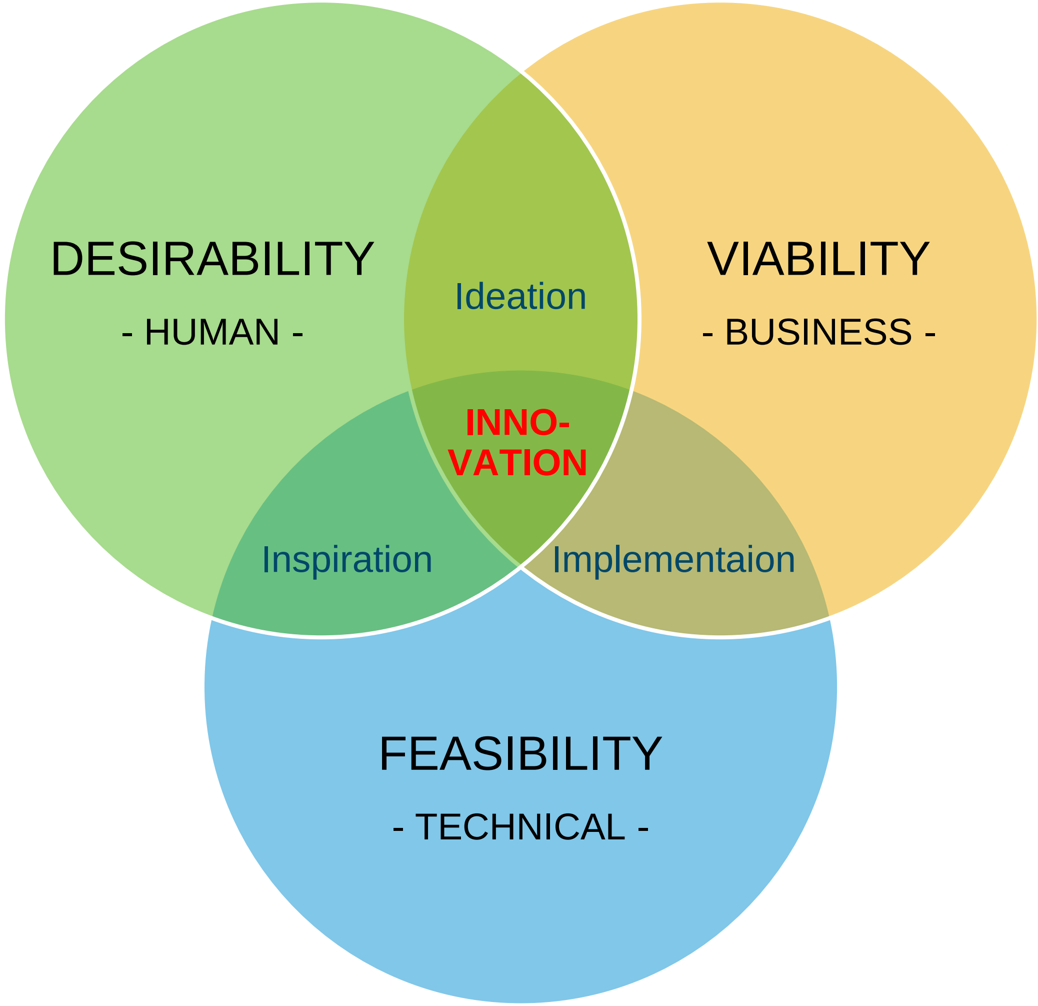
Machine Learning from an Application Point of View

The magic intersection

Well selected uses cases for machine learning can make it to successful products!

These specific use cases are usually represented as the intersection of

- **Feasibility**
- **Desirability**
- **Viability**



Machine Learning from an Application Point of View

Feasibility of machine learning use cases

Identify the **data sources** for the machine learning algorithm

- Structured data such as database tables
- Unstructured data such as images etc.
- Is historical decision data available to train your ML algorithm?

Identify how humans **process** this data in real life

- Can the users describe clearly how they come to decisions?
- Is their decision readily determined by the identified data sources?
- If users employ their social network or “gut feeling” for decisions, the selected data sources may not be sufficient

Machine Learning from an Application Point of View

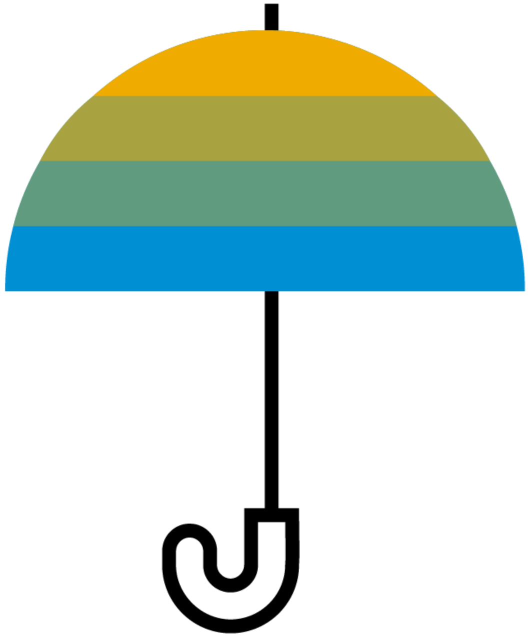
Desirability of machine learning use cases I

Only comparative advantages are convincing customers

- Can your ML algorithm solve a problem that otherwise cannot be handled by humans?
  – Then you have a **strategic** differentiator
- Can your solution take over work done today by human workforce?
  – Then you have a **cost** differentiator

<ins>Examples</ins>:

- Customers usually have a huge workforce organized in Financial Shared Service Centers (FSSCs)
- In contrast, substituting workforce in a highly specialized Treasury department might only spare a couple of human full-time equivalents

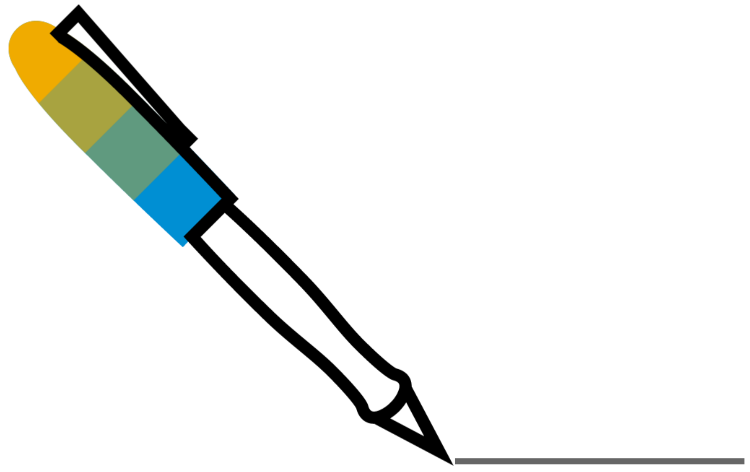


Machine Learning from an Application Point of View

Desirability of machine learning use cases II

The application of machine learning may also have limitations from a legal, ethical, or acceptance perspective

- Customers may have to explain the ML decisions to a **legal** court
- Having ML decide on a matter of life or death may be an **ethical** problem – probably a rare case in business application
- Since ML usually only provides a likelihood of correct results, irreversible decision may not find **acceptance** with a customer



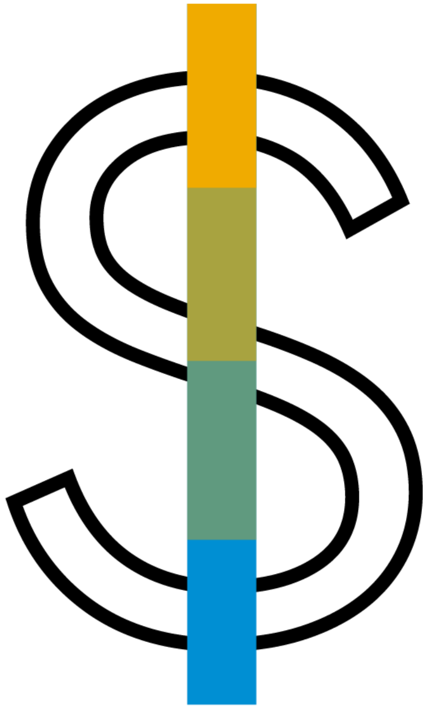
Machine Learning from an Application Point of View

Viability of machine learning use cases I

In the end, ML will only be business-viable if customers are willing to pay for it, counting also the **TCO** of applying ML

Customers are highly interested in getting better **automation** of their business; they do not care if it is done by ML or not

- Does your ML algorithm solve a use case that cannot be done by easier means?
- Example: SAP Cash Application adds to the classical accounts receivable rules in SAP S/4HANA



Machine Learning from an Application Point of View

Viability of machine learning use cases II

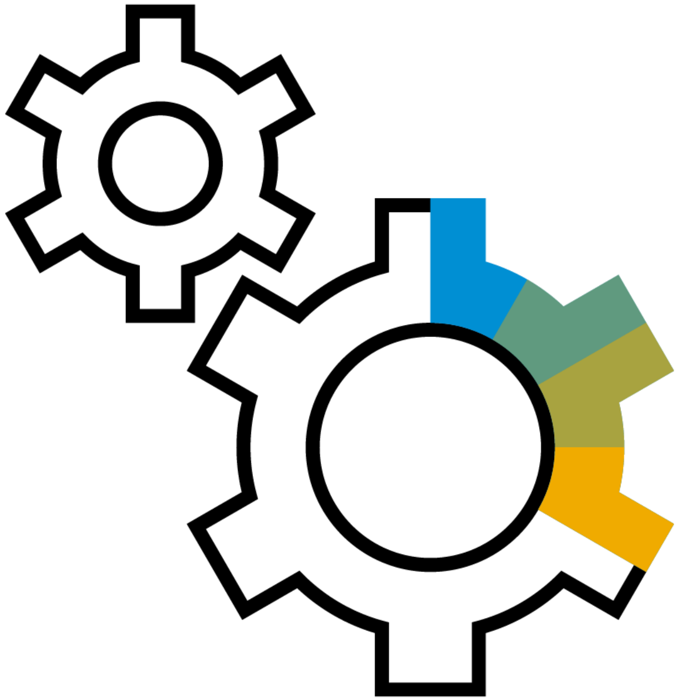
Customers think in business processes they wish to automate

An isolated ML algorithm may only be seen by customers as a “free-of-charge” process improvement

- Customers may not be willing to pay extra for it
- And without customer demand, no sales team will push the solution

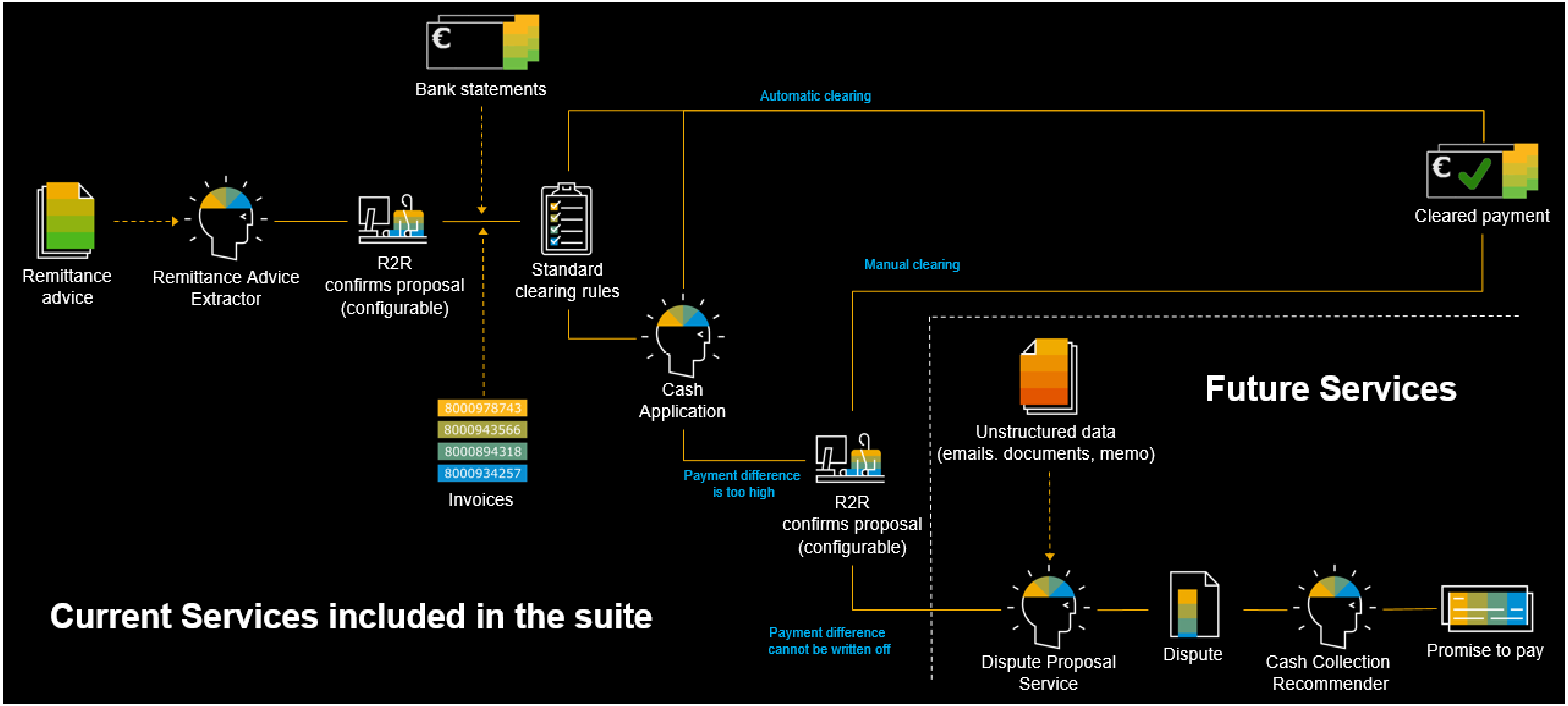
Instead, **bundle ML** with business application improvements to improve automation along an important end-to-end process!

- Best results are obtained when combining ML and application experts in one joint team
- Let’s look at the example of automating accounts receivable now



Machine Learning from an Application Point of View

End-to-end process with machine learning



Thank you.

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Week 5: Industry Applications of Deep Learning

Unit 2: Machine Learning in Customer Service

Machine Learning in Customer Service

What we'll cover…

Business Problem in Customer Service Ticketing

Applying Deep Learning

Dataset Collection

Dataset Preparation

Model Selection & Design

Model Training

Model Evaluation

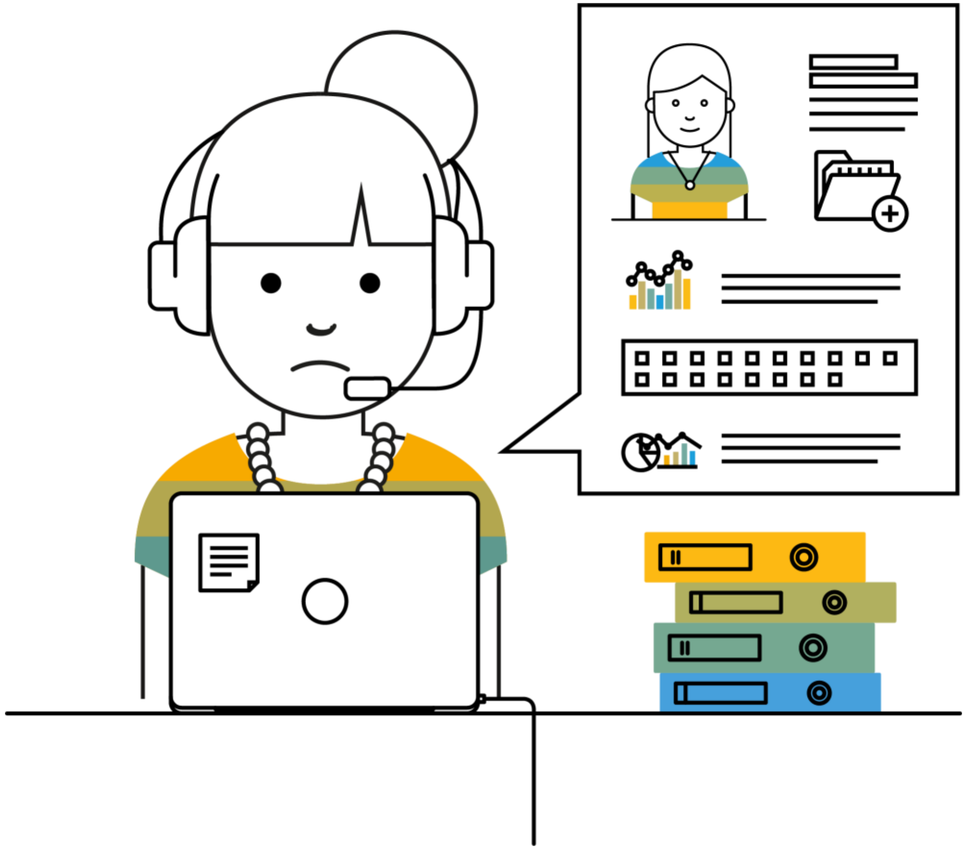
Model Testing

Putting It All Together – E2E Service Ticket Intelligence

Machine Learning in Customer Service

Between saving a customer relationship or creating unhappy experiences

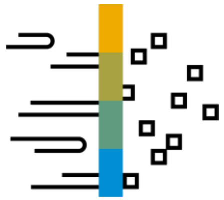
While **customer service** is critical for better customer relationships…



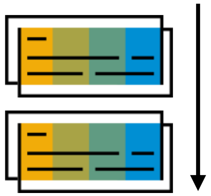
Most customer service agents today are **overwhelmed & ill-equipped**

Machine Learning in Customer Service

Between saving a customer relationship or creating unhappy experiences



High volume of incoming tickets across channels



High number of repetitive incoming tickets

High manual effort to find relevant data

“Customers who encounter positive social customer care experiences are three times more likely to recommend a brand.”

Harvard Business Review

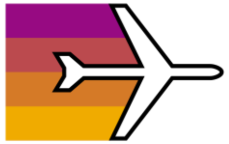
“95% of dissatisfied customers tell others about their bad experience.”

Dimensional Research

Machine Learning in Customer Service

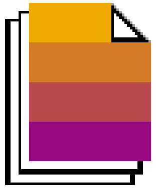
Applying deep learning by looking at past data examples to find patterns and train a model

Bel Air Customer Service Example



Airline company with contact center

100 front office customer service agents



100K messages/week via Twitter channel

Machine Learning in Customer Service

Applying deep learning by looking at past data examples to find patterns and train a model

Supervised Learning Approach

A significant amount of historical ticket data with *associated* messages, labels, and answers

Prepare data

Train model

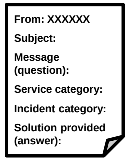
Deploy model

Capture feedback for re-training

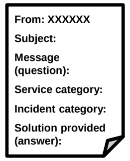
“message”

Prediction Service

“labels”



Incoming message



Ticket category predicted

Machine Learning in Customer Service

Data collection & exploration – Identifying the data source and features used for model training

Dataset summary
20k examples with associated messages and service categories

Features
Incoming Twitter messages
are represented via features learned by deep learning

Labels
Service categories are known as labels

Machine Learning in Customer Service

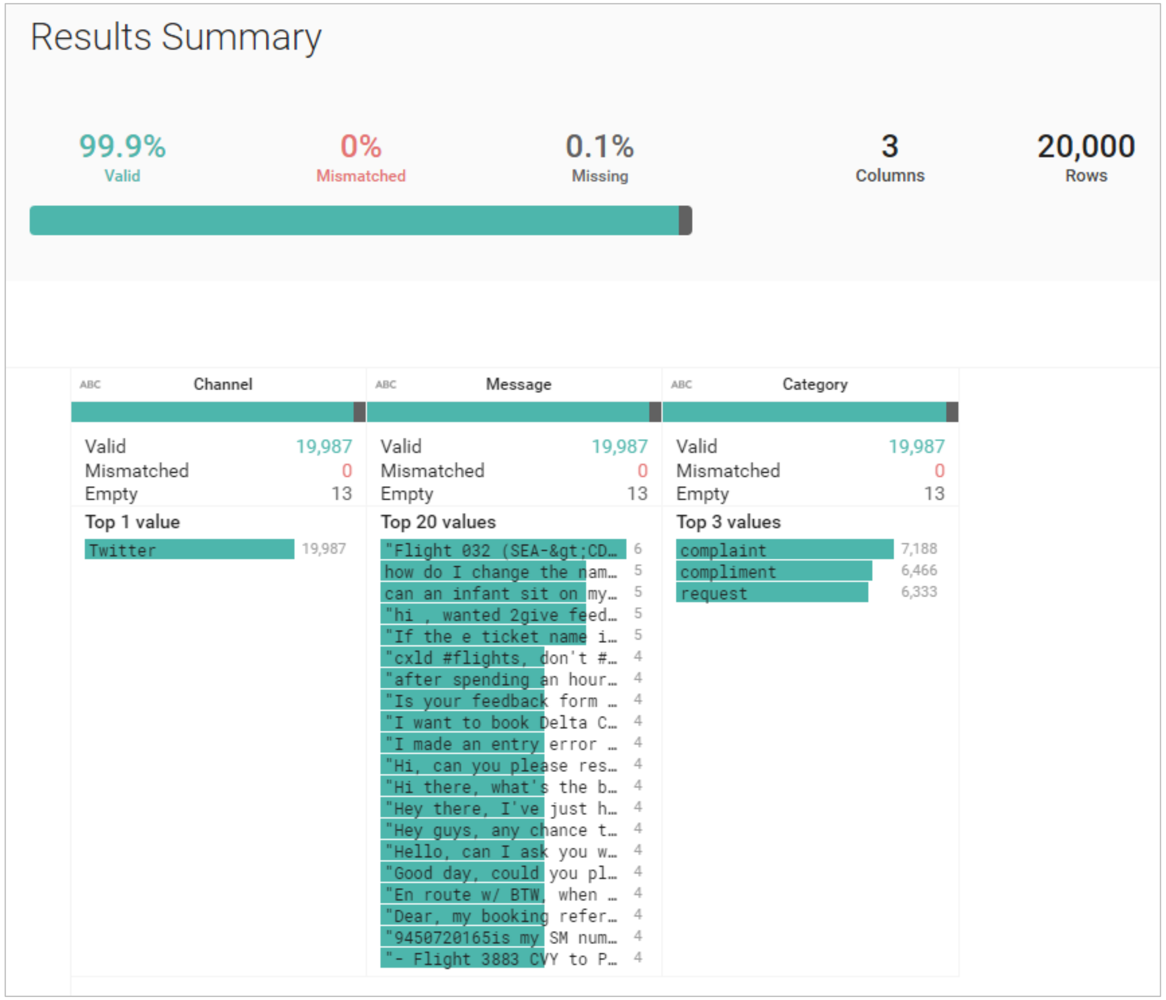
Prepare raw data by cleaning, transforming it for model training

Data Cleansing

- Check if the data is clean and without any duplicates
- Check if the data does not contain any missing values or outliers

Data Exploration

- Check if there are sufficient examples on each label category



Machine Learning in Customer Service

Model selection – Comparing prediction accuracy for various models across data sets

Method	AG	Sogou	DBP	Yelp Po	Yelp Full	Amz Full	Amz Po
Dataset size (1000)	120	450	560	560	650	3000	3600
Traditional Methods							
BoW	88.81	92.85	96.61	92.24	57.91	54.64	90.40
TF-IDF (text frequency)	89.64	93.45	97.36	93.66	59.86	55.26	91.00
Word-Based Models							
Bag-of-Means	83.09	89.21	90.45	87.33	52.54	44.13	81.61
Word Convolution	88.65	95.46	98.29	94.44	57.87	57.41	94.00
Character-Based Models							
Character Convolution	**90.51**	**96.17**	**98.72**	**94.81**	**61.62**	**60.02**	**95.08**

Machine Learning in Customer Service

Service ticket workflow with deep learning

Incoming Service Tickets

Just had an excellent display of customer service – super helpful. Resolved our issue!

My suitcase was damaged, how can I make a claim for a repair?

Waiting for over an hour for the service person to show up. Getting tired!

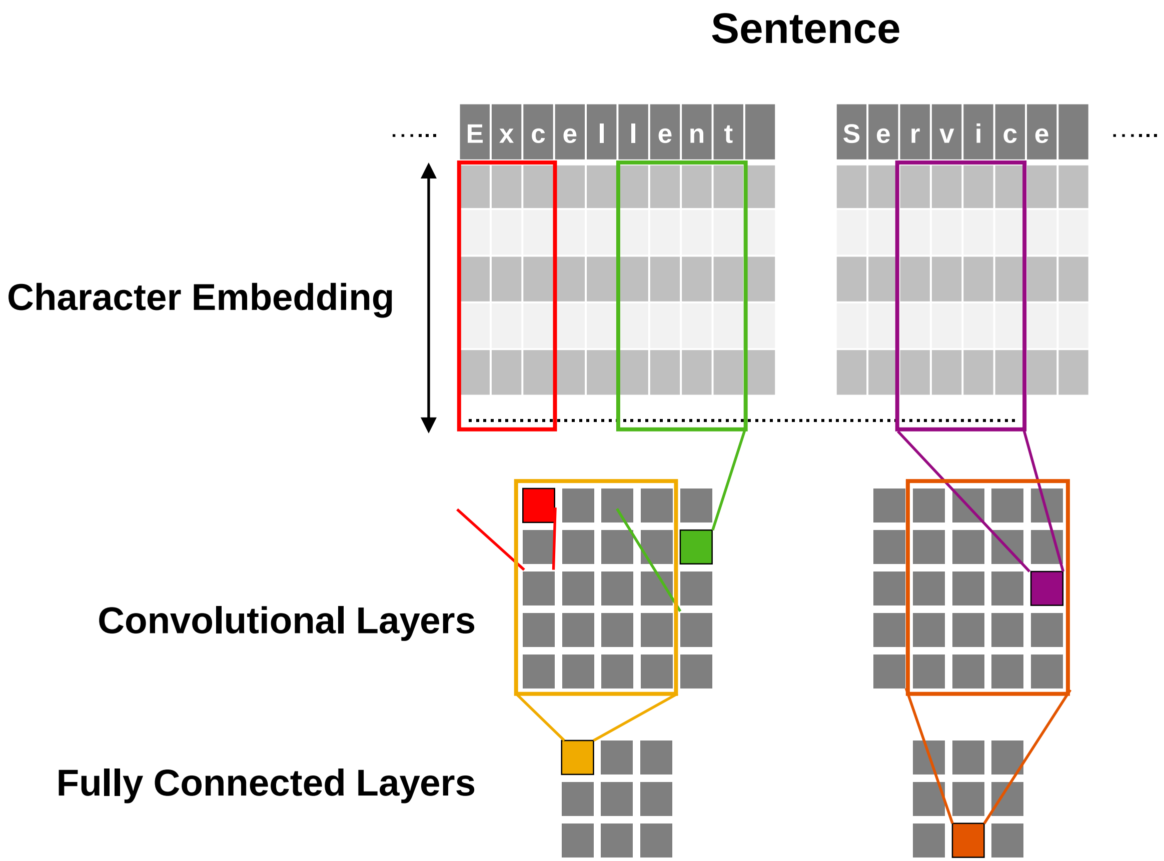
Neural Network Model

Ticket Classification Result

Compliment	Request	Complaint
0.91	0.06	0.03
0.04	0.75	0.21
0.05	0.25	0.70

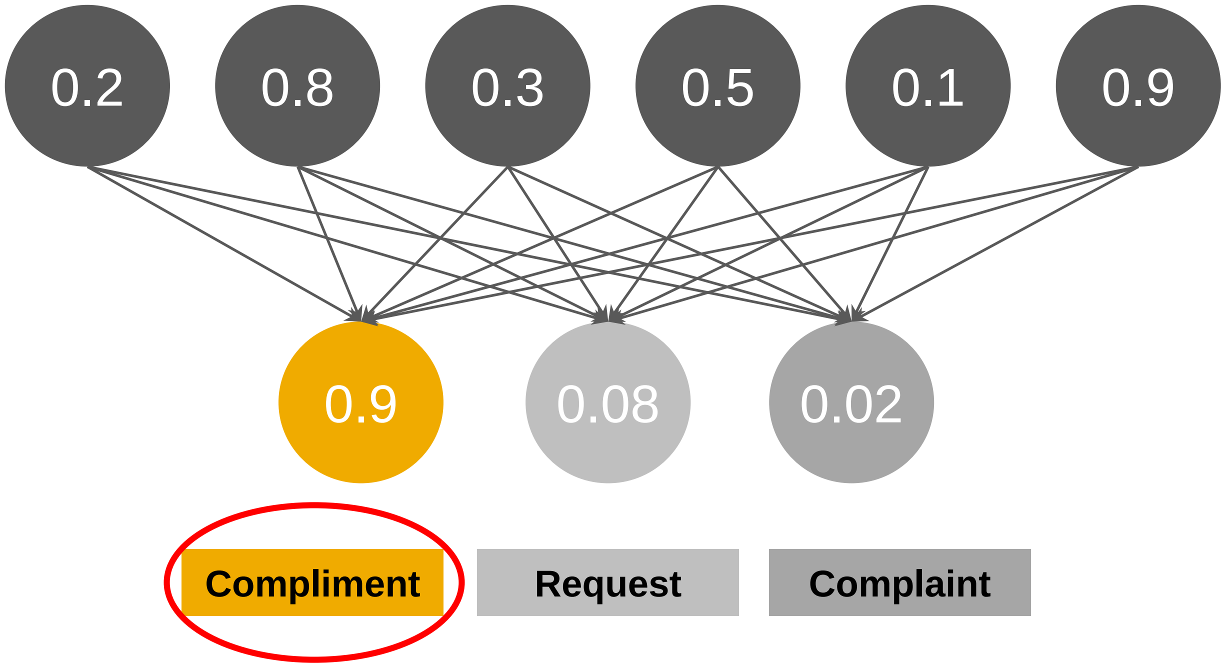
Machine Learning in Customer Service

Convolutional neural network for text classification with character-level embedding



Machine Learning in Customer Service

Predict category based on text vector representation

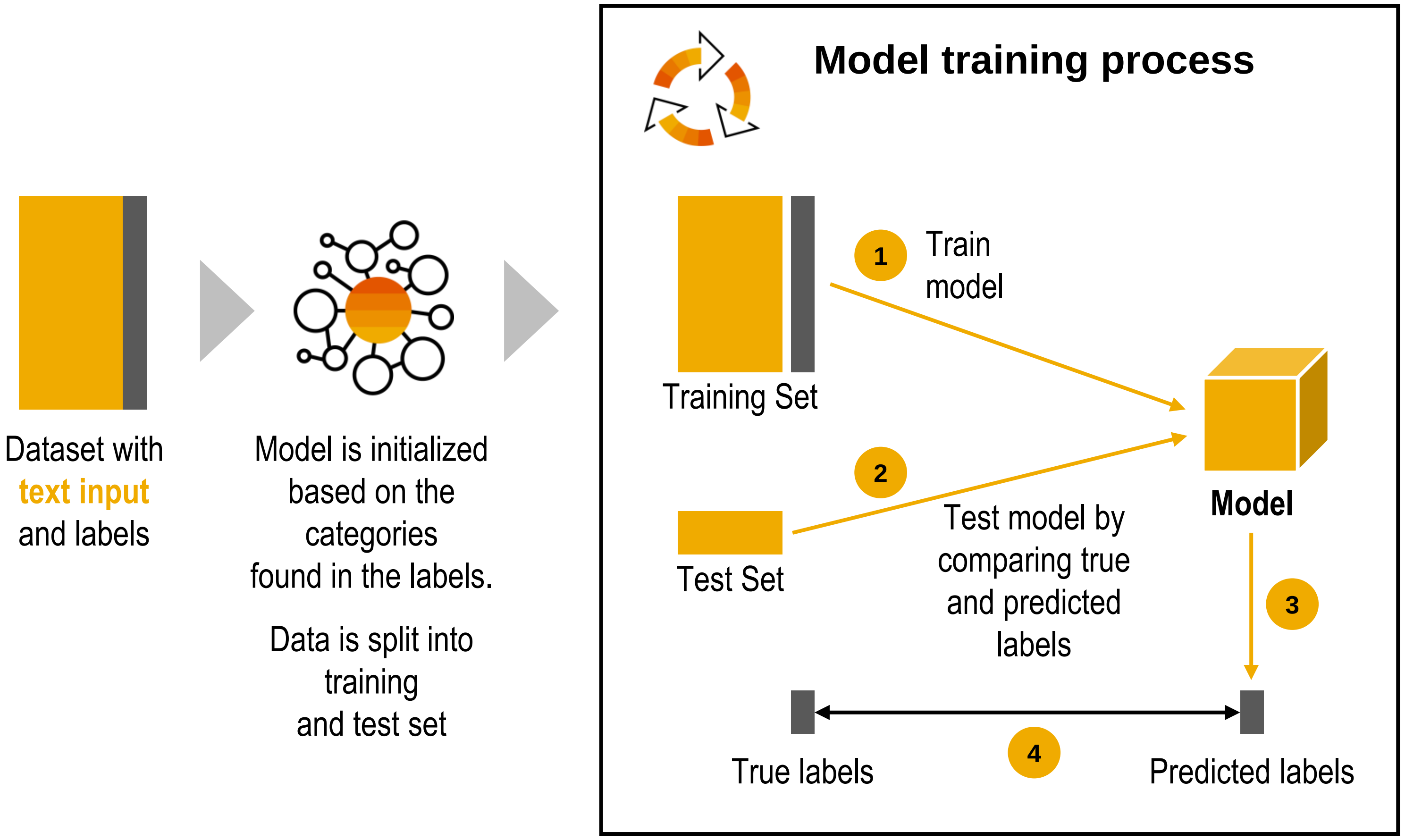


Representations learned from neural network

Output layer (softmax activation)

Machine Learning in Customer Service

Model training – Creating a model using prepared dataset



Training

- Data is split into training and validation set
- Training data set is used for learning the model
- Test data set is used to evaluate the model performance

Machine Learning in Customer Service

Model evaluation – Gauge performance of model before productive deployment

Confusion Matrix commonly accepted framework for performance evaluation of model.

Key metrics are:

- Accuracy: Overall, how often is the classifier correct?
- Recall: proportion of positive predictions that are correct
- Precision: proportion of true negatives that are correct

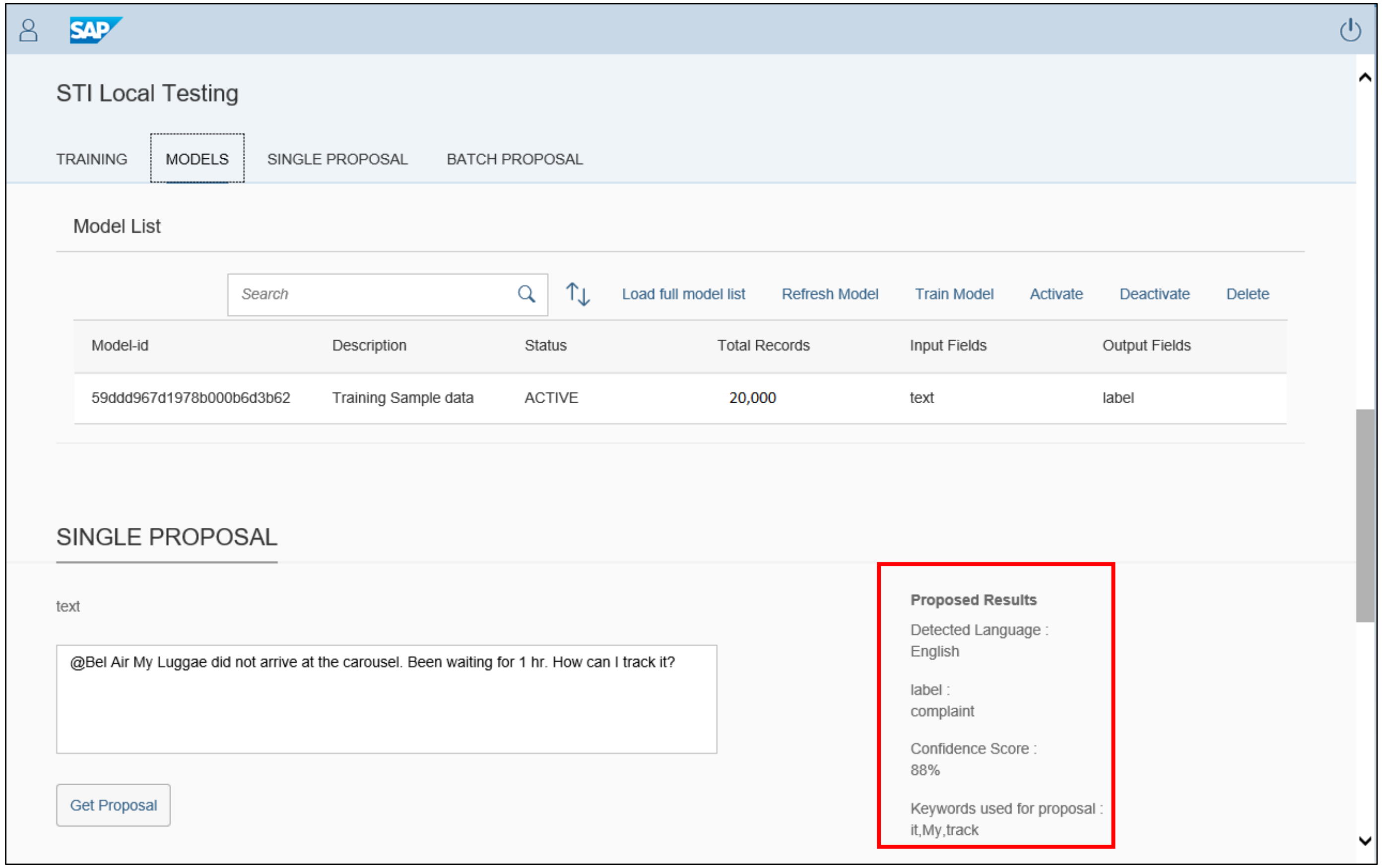
	Precision	Recall	F1
Request	0.90	0.86	0.88
Complaint	0.82	0.86	0.84
Compliment	0.89	0.89	0.89
Average / Total	0.87	0.87	0.87
Test Accuracy	86.75%		

Machine Learning in Customer Service

Model testing – Use sample inputs to test drive the model

Offline testing

- Test the Service Category prediction API with sample inputs
- Check prediction results – label, confidence score, keywords used for prediction



Jack Mayer

Bel-Air Customer

Jenny Smith

Service Agent

Jack Mayer

Bel-Air Customer

Jenny Smith

Service Agent

Thank you.

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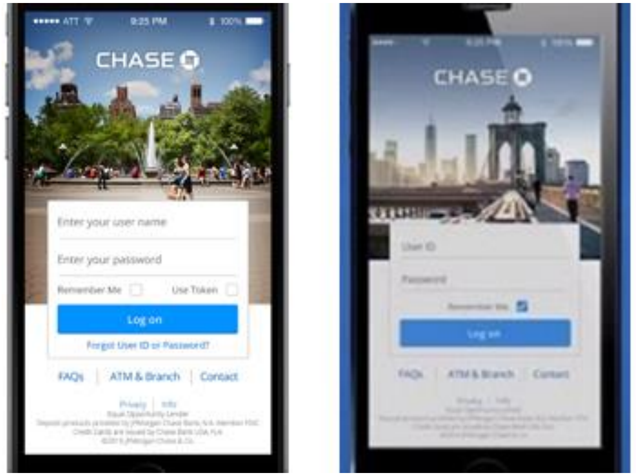
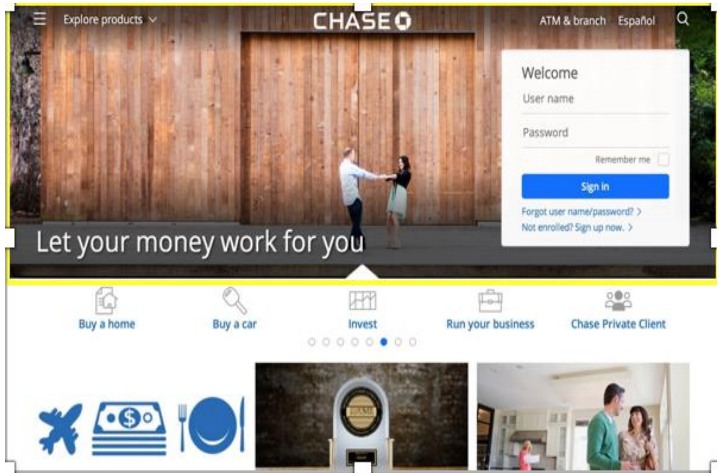
Week 5: Industry Applications of Deep Learning

Unit 3: Machine Learning in Banking

Machine Learning in Banking

Personalizing Chase’s digital channels





Experience Personalization

- Location-based background image

Ad Targeting

- Providing the best offers for our customers on Chase-owned domains

Paid Media Targeting

- Targeting on Web sites external to Chase

Machine Learning in Banking

Examples of our use cases and the power of machine learning

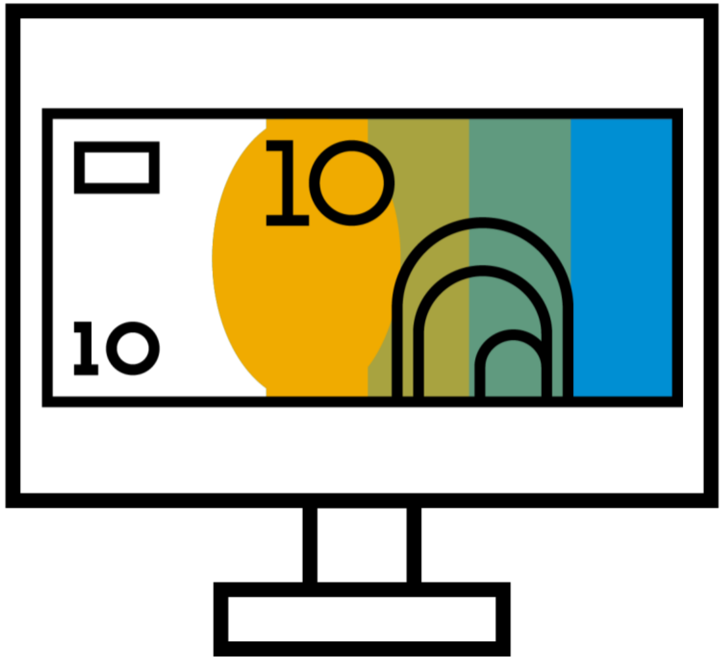
Retail banking applications

- Fraud detection
- Credit scoring
- Image processing

Machine Learning in Banking
What's different?

Do we use ML in banking?

- What has changed?
  – Then vs. now
- What is different about FinTech?
  – Government regulation and compliance
  – Higher exposure to risk

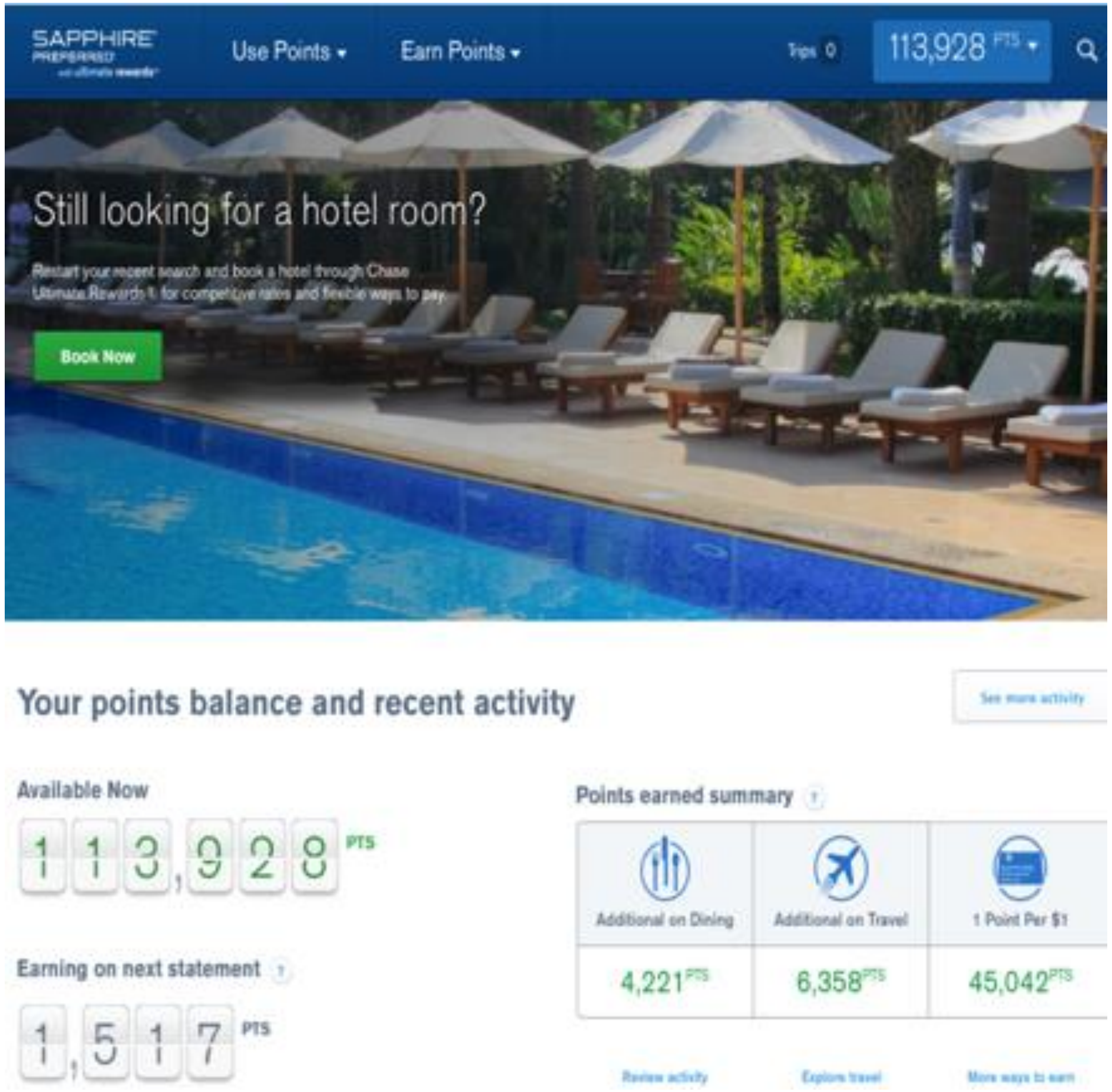


Machine Learning in Banking

Recommender systems

Personalized ad targeting on ultimaterewards.com through the power of recommendations

- Increase site engagement by targeting redemption option most likely to appeal to the consumer
- Gift cards and travel destinations
- Improve user experience while reducing cost for the firm



Machine Learning in Banking

Recommender systems

Framing the problem as matrix completion

- Users are Chase’s customer basis, items can be ads or messaging
- Users do not rate ads explicitly, so user rating values are implicit
- Define objective function to encompass both cost and engagement

	i_1	i_2	i_3	i_4	i_5	i_6
U1	4	?	3	?	5	?
U2	?	2	?	?	4	1
U3	?	?	1	?	2	5
U4	?	?	3	?	?	1
U5	1	4	?	?	2	5
U6	5	?	2	1	?	4
U7	?	2	3	?	4	5

Thank you.

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Week 5: Industry Applications of Deep Learning

Unit 4: Medical Image Segmentation with Fully-Convolutional Networks

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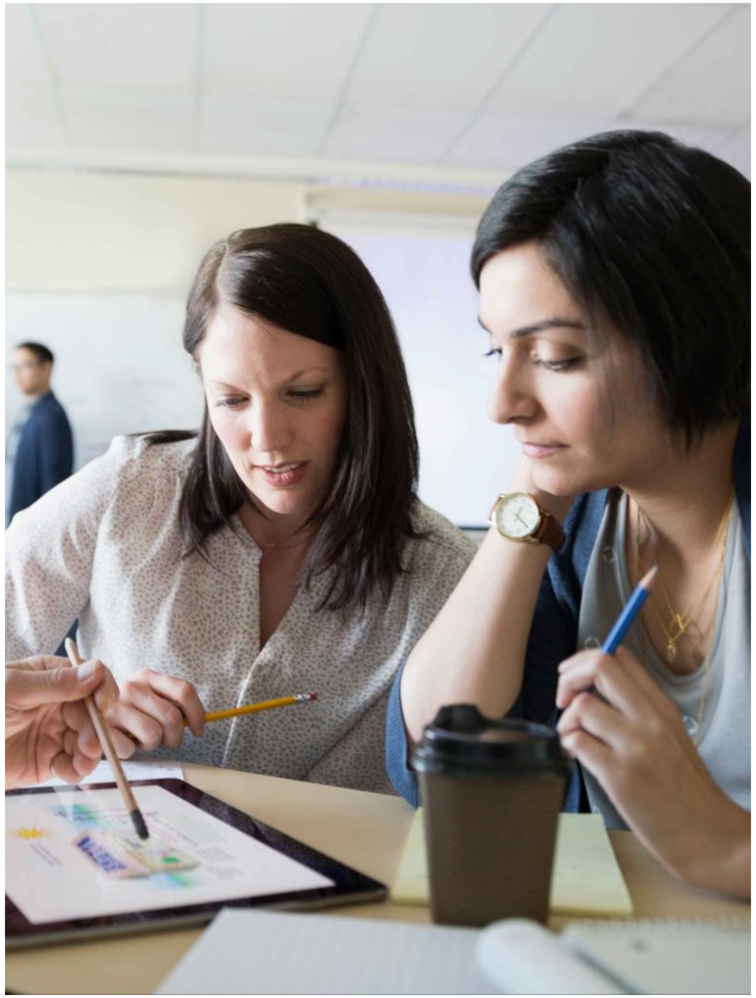
Medical Image Segmentation with Fully-Convolutional Networks

Overview

Contents

- What is medical image segmentation?
- What are fully-convolutional networks (FCNs)?
- How do we use deep learning for medical image segmentation?



Medical Image Segmentation with Fully-Convolutional Networks

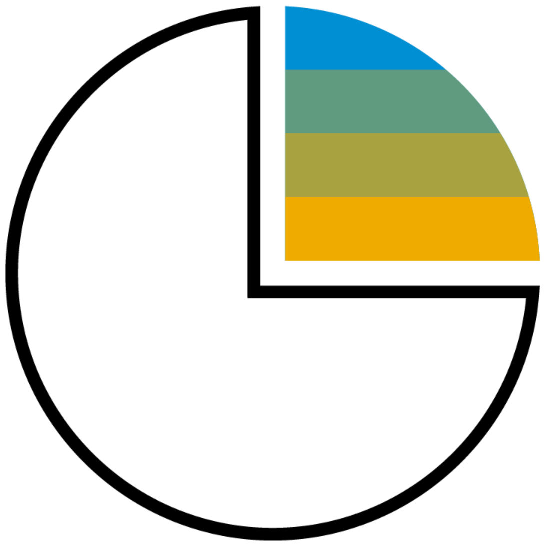
What is medical image segmentation?

Medical Imaging

- How can we look and see inside the body?
- How can we identify body parts that are working or not working?
- How can we identify things that should not be there (disease)?

Medical Image Data

- 3/4 dimensional images
  (width x height x depth x channels/time)
- Collected with physical measurements
  (X-rays, MRI,...)



Medical Image Segmentation with Fully-Convolutional Networks

What is medical image segmentation?

3D Medical Image Volumes

- Typically view image through cross-sectional planes
- Axial, coronal sagittal
- Each pixel represents intensity recorded by measurement devices

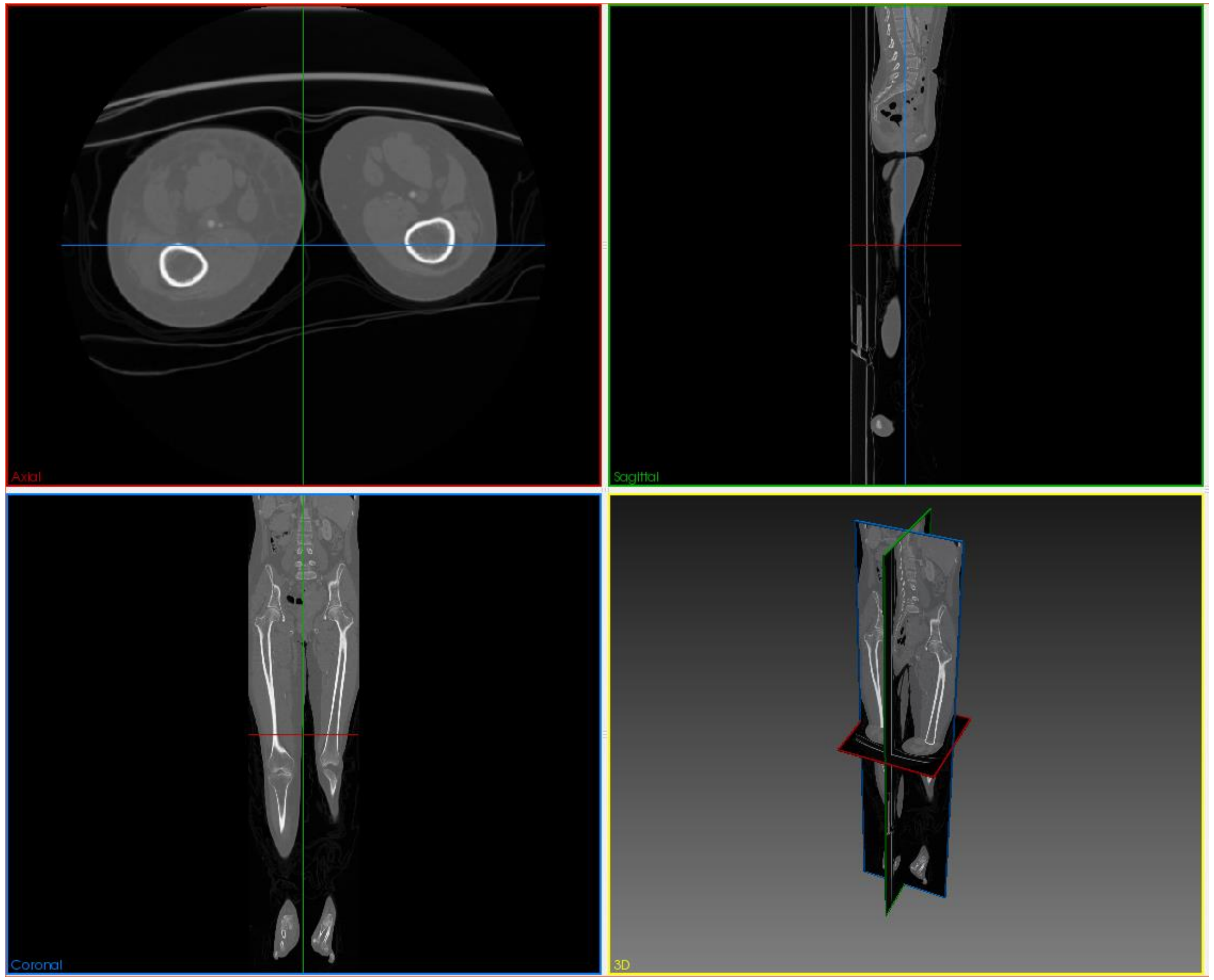


Image made using SimVascular
Simvascular.github.io

Medical Image Segmentation with Fully-Convolutional Networks

What is medical image segmentation

Medical Image Segmentation

- Exactly identify the region of interest by labeling all pixels

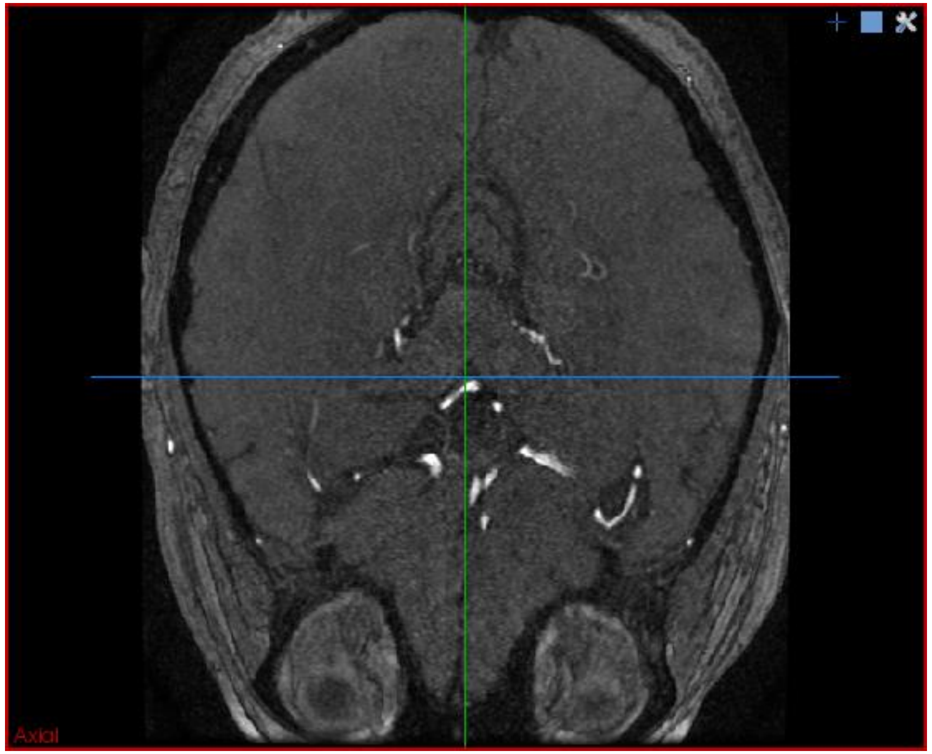


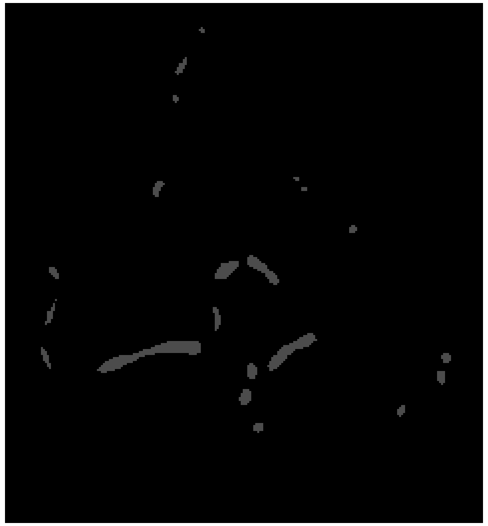
Image Classification

Aneurysm/No Aneurysm?

Image Segmentation

Pixel value 0 = Not blood vessel

Pixel value 1 = Blood vessel

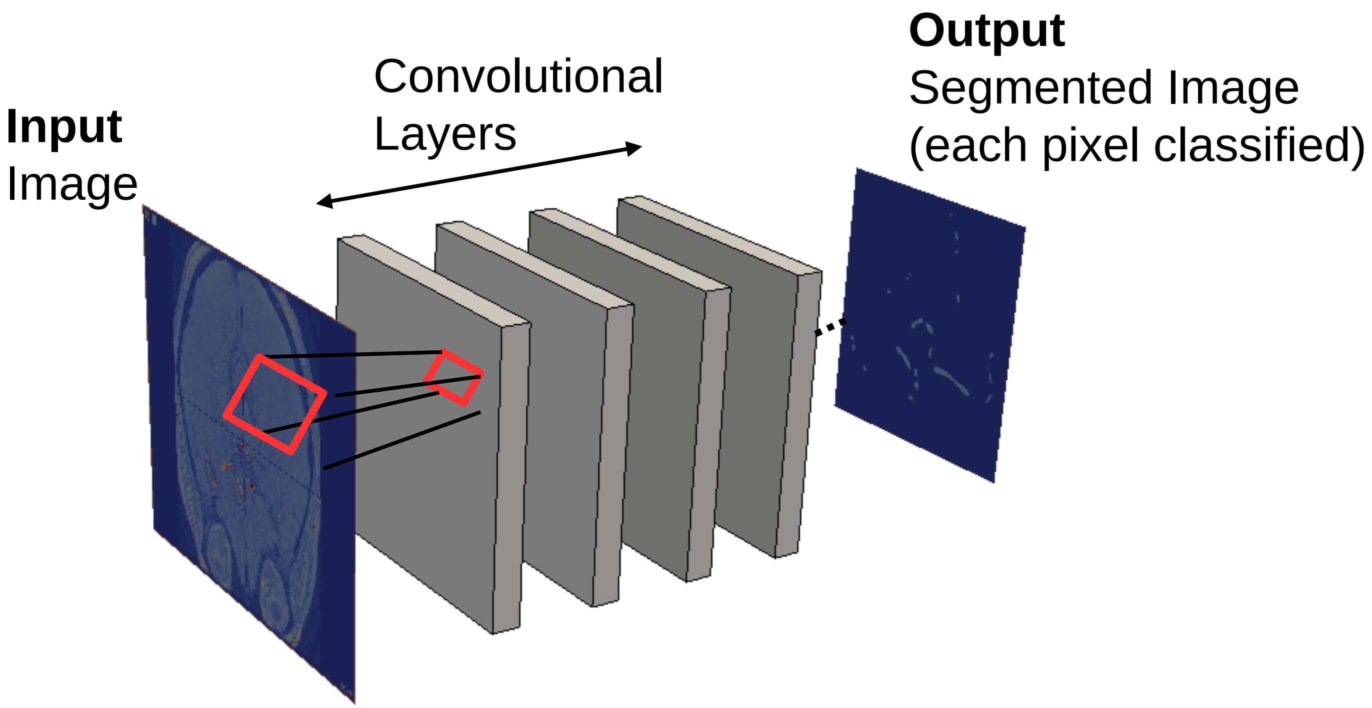


Medical Image Segmentation with Fully-Convolutional Networks

What are fully-convolutional networks?

Fully-Convolutional Networks

- Neural networks consisting primarily of convolutional layers
- **Input and output are images**
- Not like regular classification where output is a number/vector



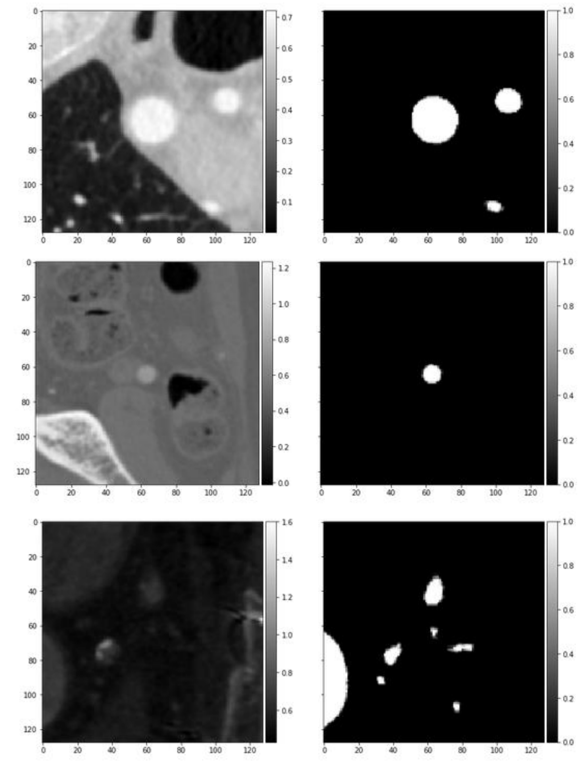
Medical Image Segmentation with Fully-Convolutional Networks

How do we use deep learning for medical image segmentation?

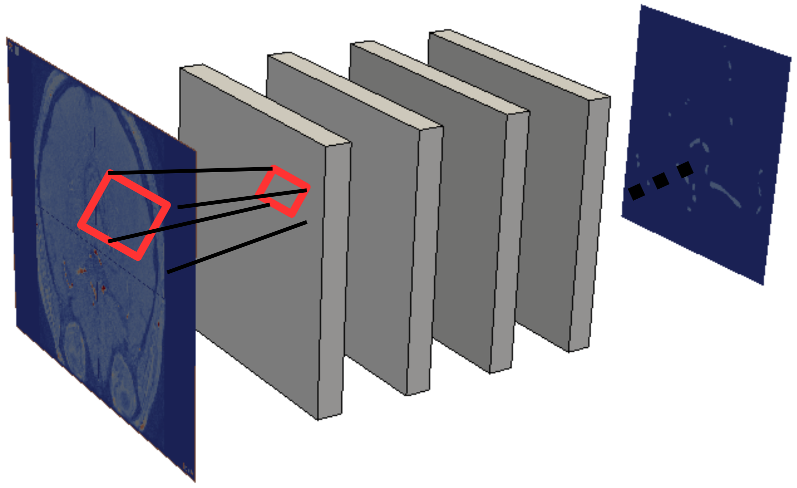
Supervised Deep Learning for Image Segmentation

- Treat the problem of image segmentation as a supervised learning problem
- Inputs are image slices/patches
- Outputs are labeled/segmented image
- For the model we use an FCN

Labeled Segmentation Data



Model FCN



Medical Image Segmentation with Fully-Convolutional Networks

Applied example

- Multimodal Brain Tumor Image Segmentation Benchmark

Thank you.

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