

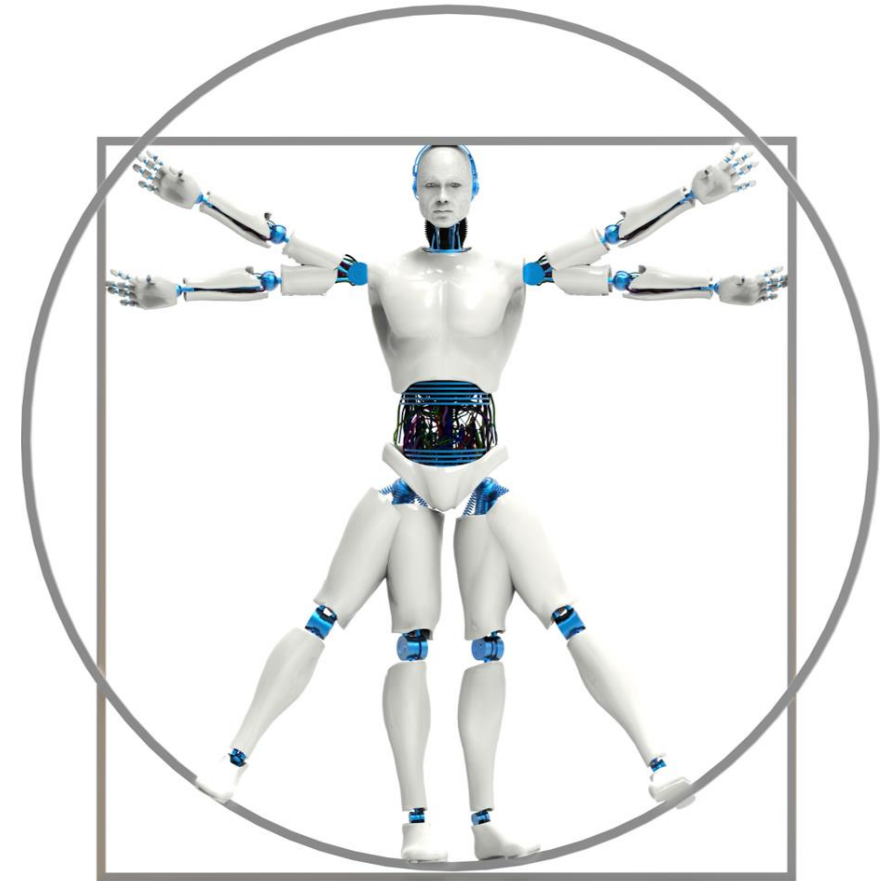
## Week 5: Industry Applications of Deep Learning

### **Unit 1: Machine Learning from an Application Point of View**

# 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



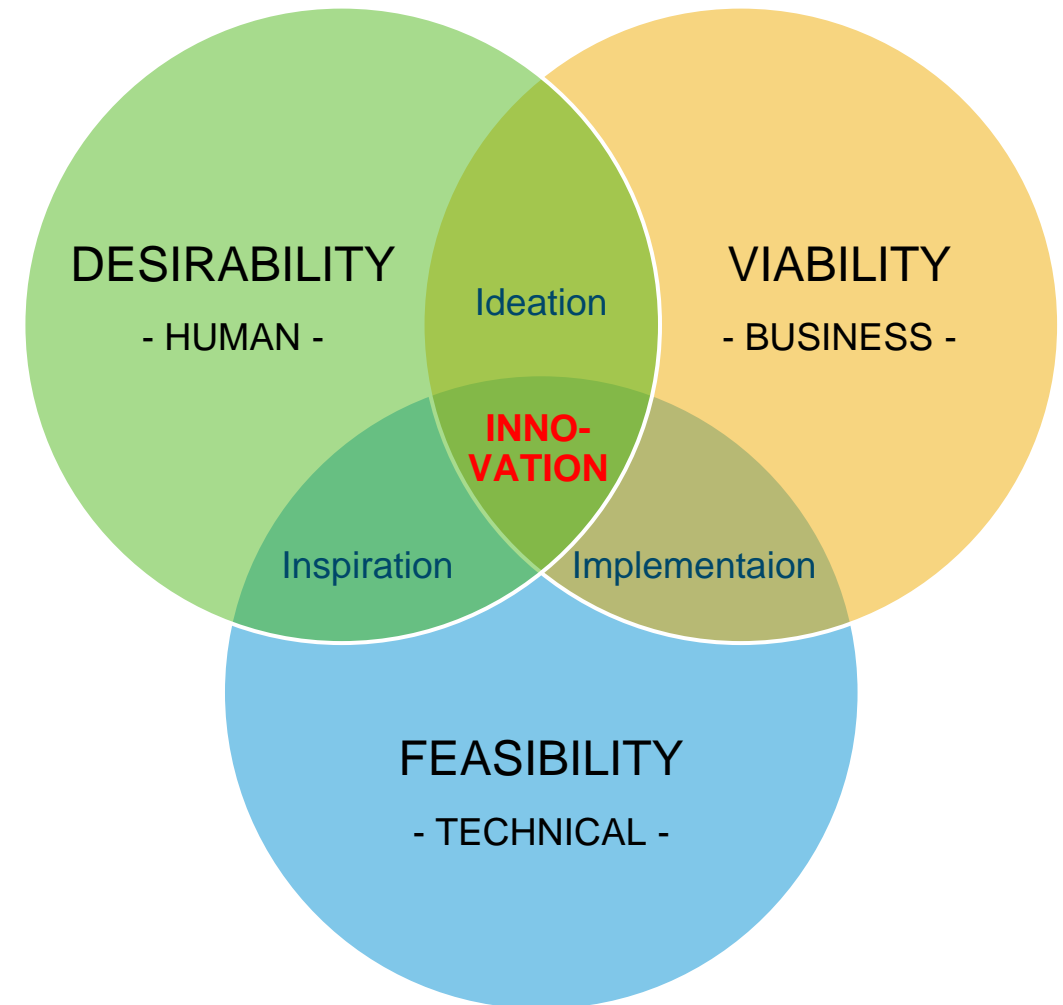
# Machine Learning from an Application Point of View

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

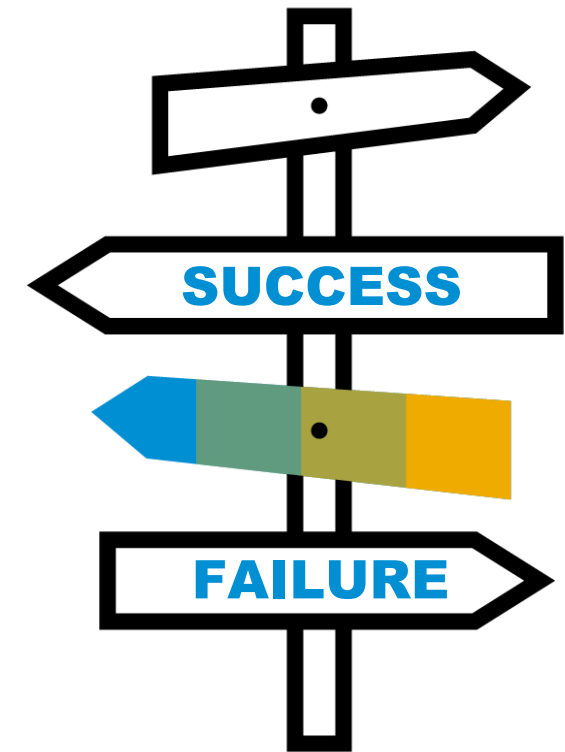
Feasibility of machine learning use cases

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

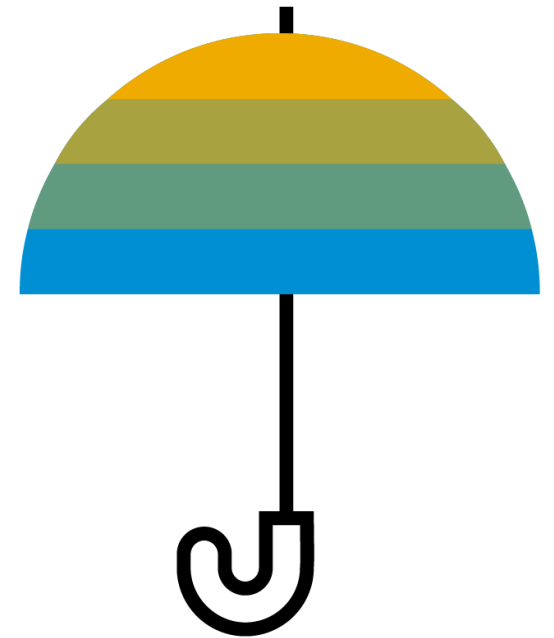
Desirability of machine learning use cases I

## 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

### Examples:

- 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

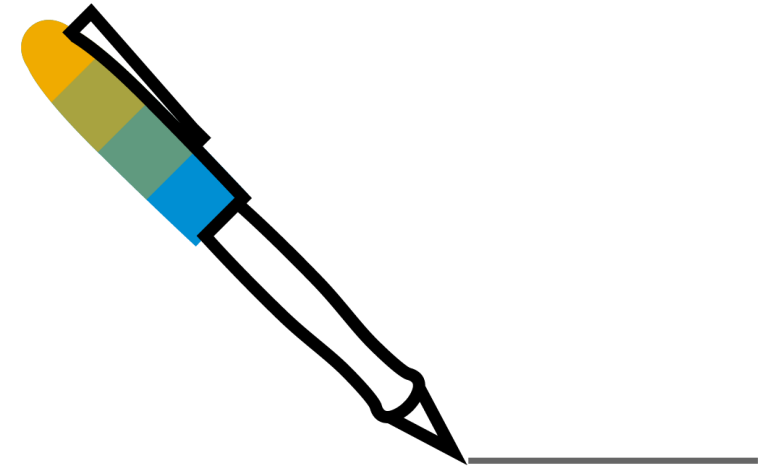


# Machine Learning from an Application Point of View

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



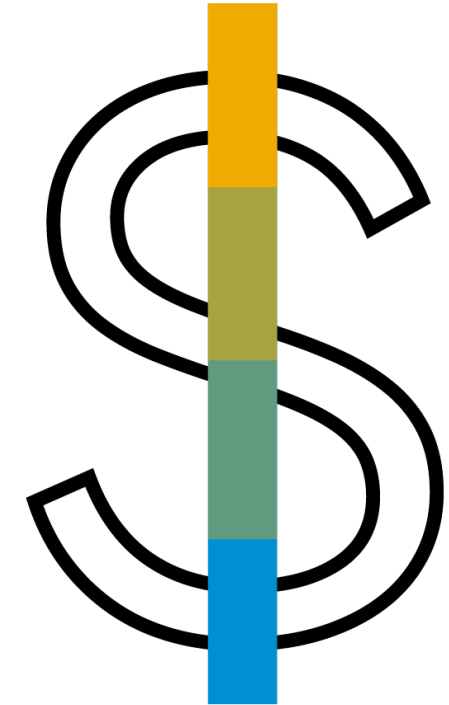
# Machine Learning from an Application Point of View

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

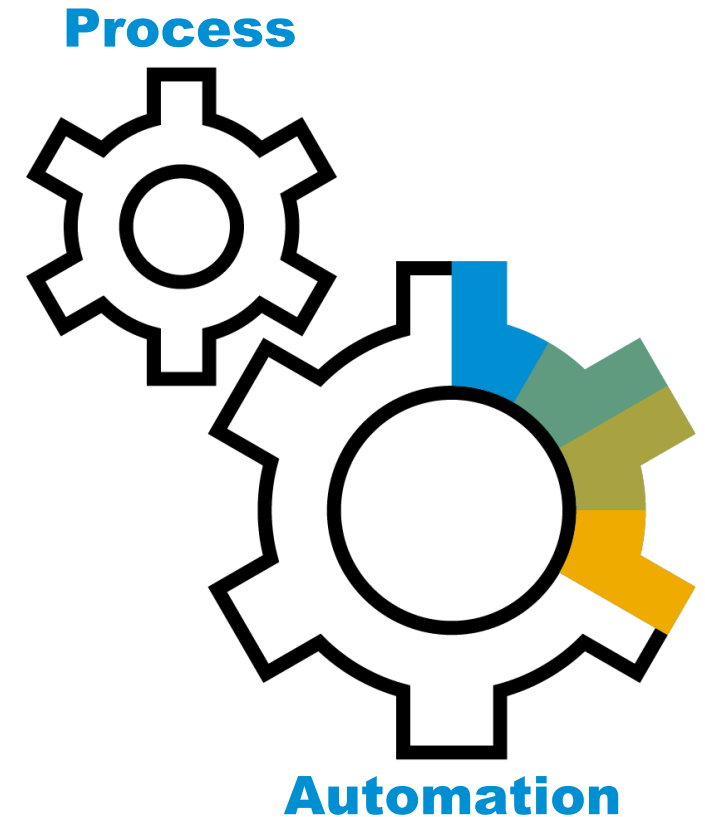
Customers think in business processes they wish to automate

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!

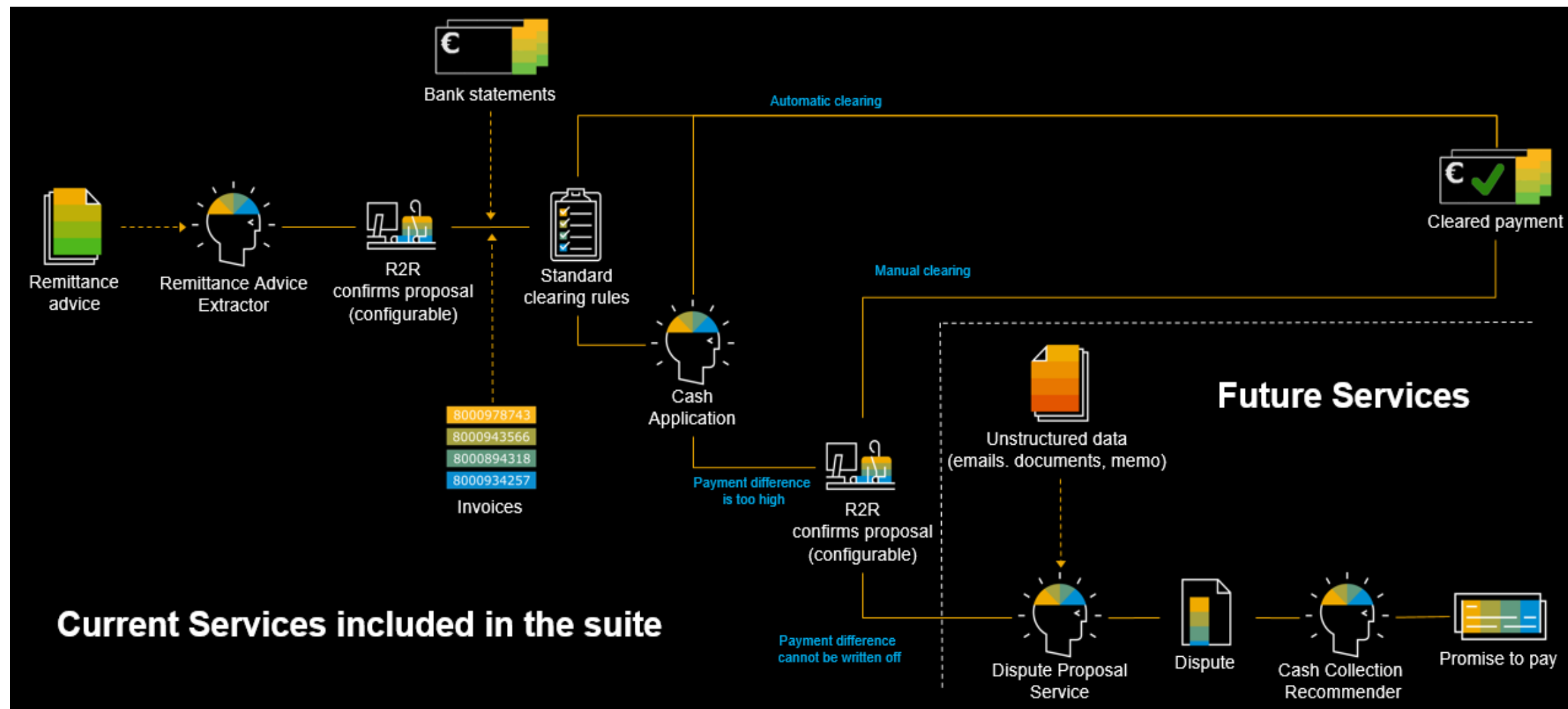
- Best results are obtained when combining ML and application experts in one joint team
- Let's look at the example of automating accounts receivable now





# Machine Learning from an Application Point of View

End-to-end process with machine learning



# Thank you.

**Contact information:**

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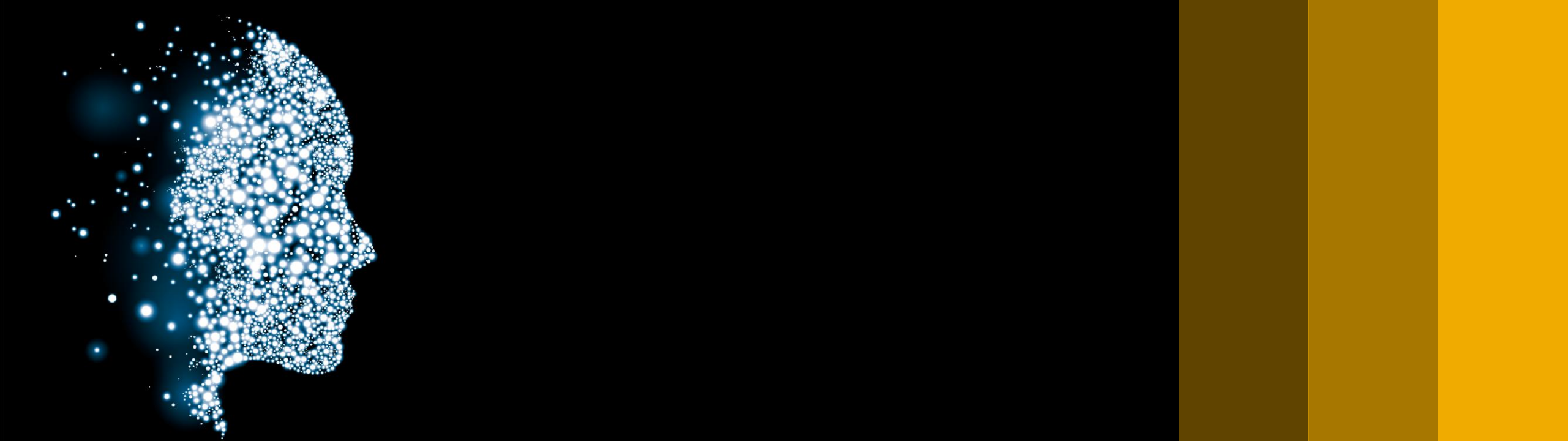
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Week 5: Industry Applications of Deep Learning

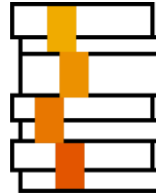
## Unit 2: Machine Learning in Customer Service

# Machine Learning in Customer Service

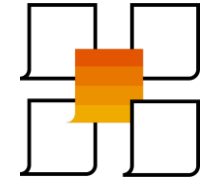
What we'll cover...



**Business Problem in  
Customer Service Ticketing**



**Applying  
Deep Learning**



**Putting It All Together – E2E  
Service Ticket Intelligence**

**Model  
Testing**

**Model  
Evaluation**

**Model  
Training**

**Model Selection  
& Design**

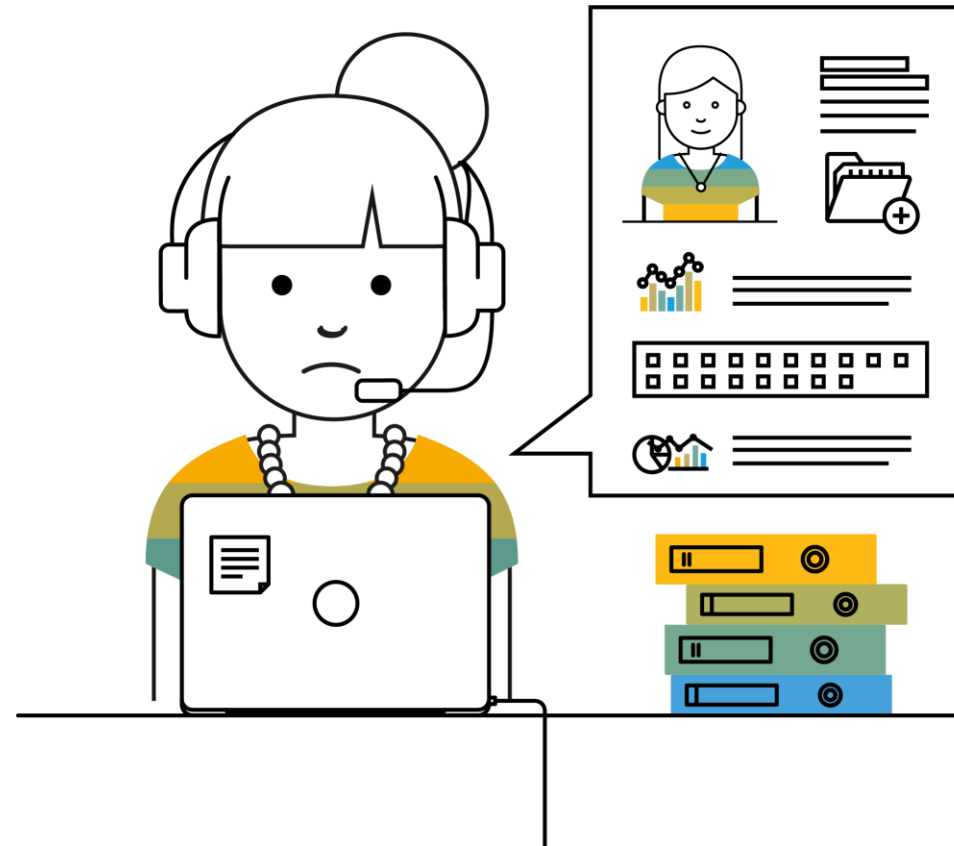
**Dataset  
Preparation**

**Dataset  
Collection**

# Machine Learning in Customer Service

Between saving a customer relationship or creating unhappy experiences

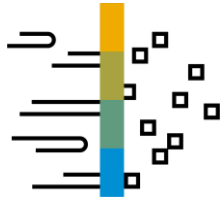
While **customer service** is critical for better customer relationships...



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

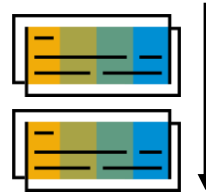
# Machine Learning in Customer Service

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*

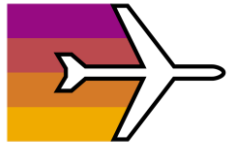
**“**95%** of dissatisfied customers tell others about their bad experience.”**

*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**



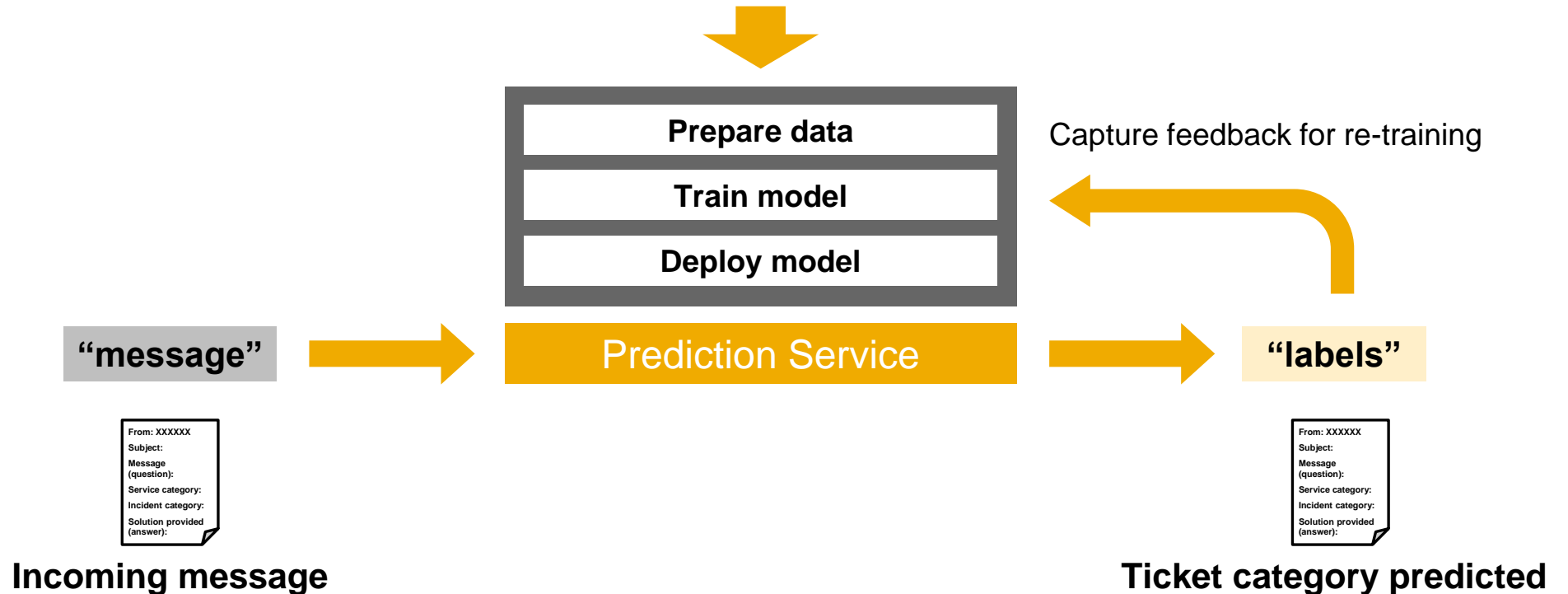
# Machine Learning in Customer Service

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



# 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

### Results Summary

99.9%  
Valid

0%  
Mismatched

0.1%  
Missing

3  
Columns

20,000  
Rows

ABC	Channel	ABC	Message	ABC	Category
Valid	19,987	Valid	19,987	Valid	19,987
Mismatched	0	Mismatched	0	Mismatched	0
Empty	13	Empty	13	Empty	13
Top 1 value		Top 20 values		Top 3 values	
Twitter 19,987		"Flight 032 (SEA->CD... 6		complaint 7,188	
		how do I change the nam... 5		compliment 6,466	
		can an infant sit on my... 5		request 6,333	
		"hi , wanted 2give feed... 5			
		"If the e ticket name i... 5			
		"cxld #flights, don't #... 4			
		"after spending an hour... 4			
		"Is your feedback form ... 4			
		"I want to book Delta C... 4			
		"I made an entry error ... 4			
		"Hi, can you please res... 4			
		"Hi there, what's the b... 4			
		"Hey there, I've just h... 4			
		"Hey guys, any chance t... 4			
		"Hello, can I ask you w... 4			
		"Good day, could you pl... 4			
		"En route w/ BTW, when ... 4			
		"Dear, my booking refer... 4			
		"9450720165is my SM num... 4			
		"- Flight 3883 CVY to P... 4			

# 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
<b>Traditional Methods</b>							
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
<b>Word-Based Models</b>							
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
<b>Character-Based Models</b>							
Character Convolution	<b>90.51</b>	<b>96.17</b>	<b>98.72</b>	<b>94.81</b>	<b>61.62</b>	<b>60.02</b>	<b>95.08</b>


# 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

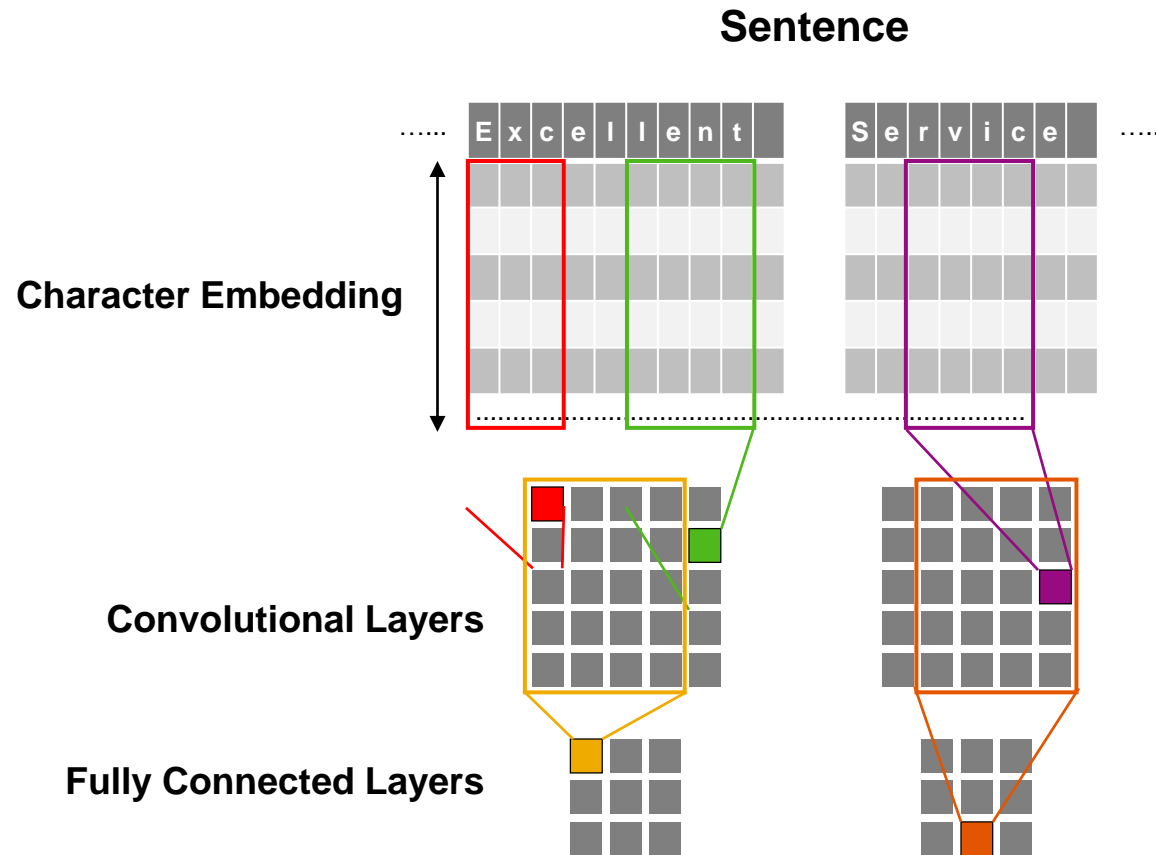


## Ticket Classification Result

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

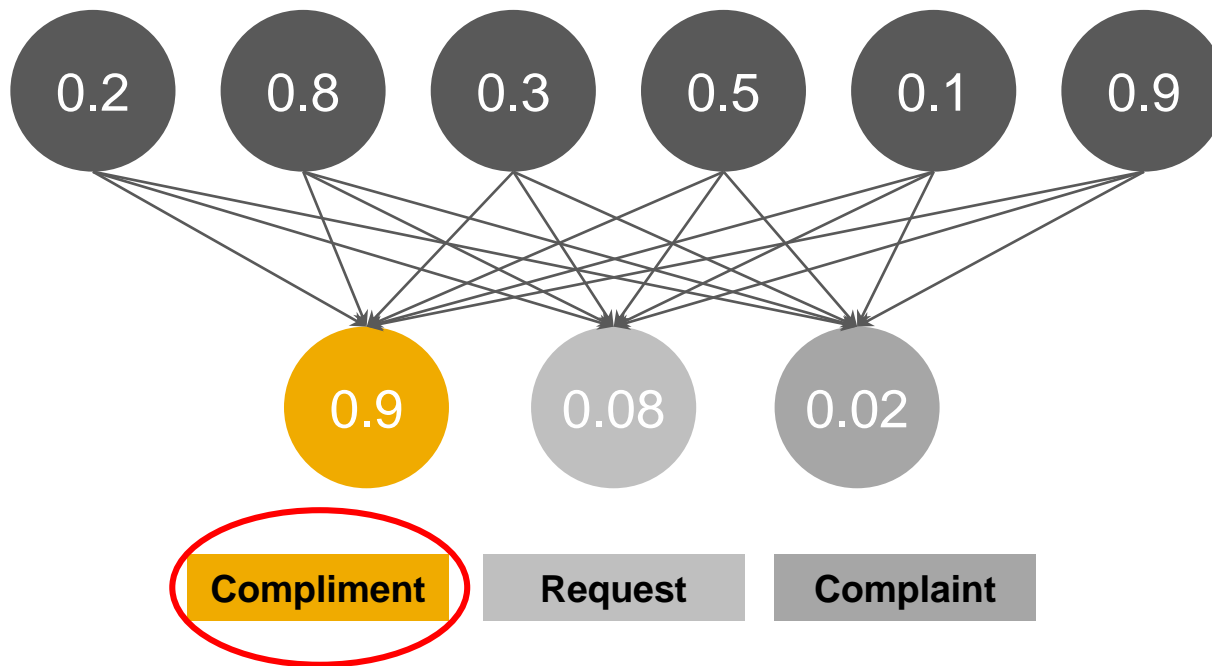
# Machine Learning in Customer Service

Convolutional neural network for text classification with character-level embedding



# Machine Learning in Customer Service

Predict category based on text vector representation

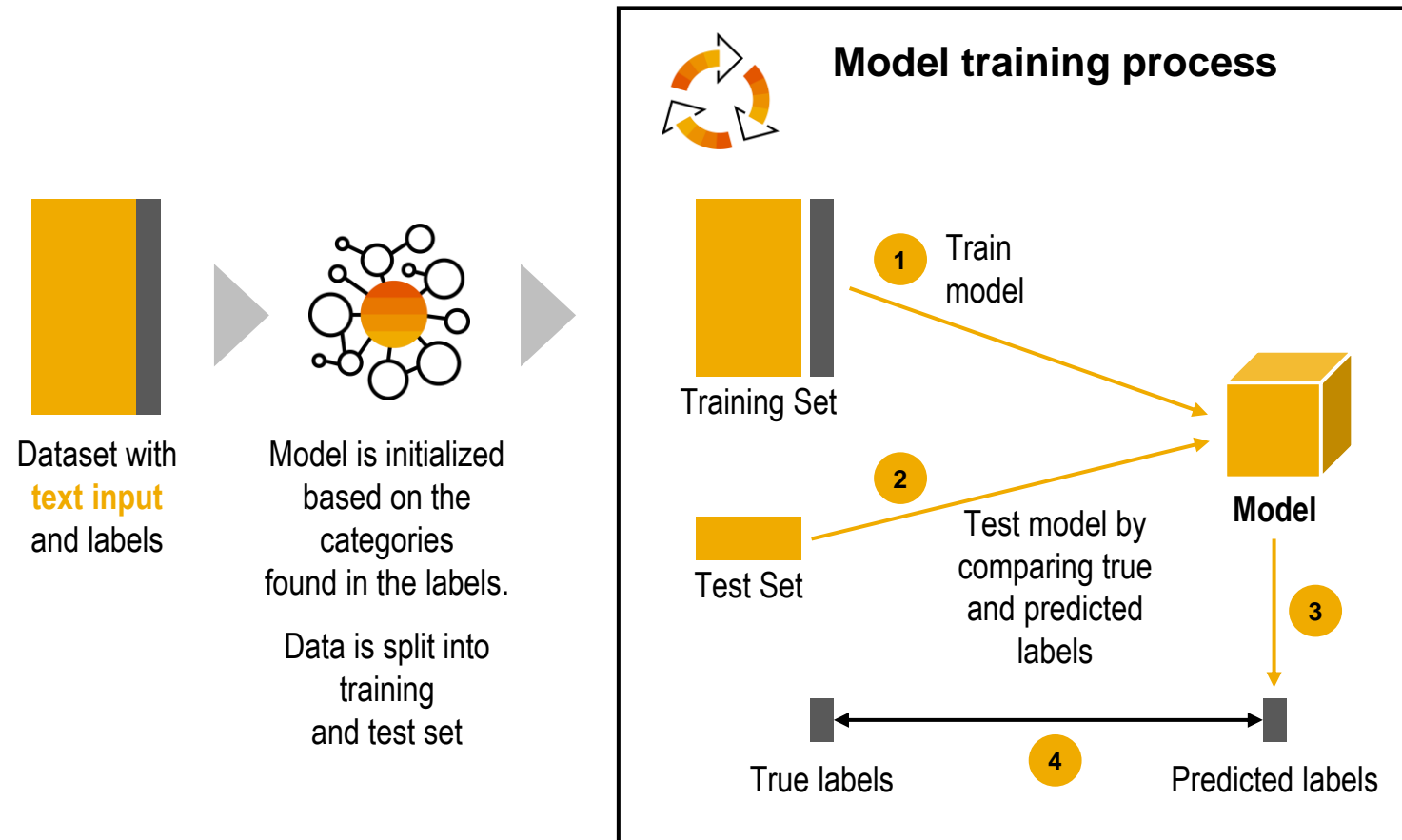


Representations learned from neural network

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

The screenshot displays the SAP STI Local Testing interface. At the top, there's a header with the SAP logo and a user icon. Below the header, the title 'STI Local Testing' is followed by four tabs: 'TRAINING', 'MODELS' (which is selected and highlighted with a dashed border), 'SINGLE PROPOSAL', and 'BATCH PROPOSAL'.

Under the 'MODELS' tab, there's a 'Model List' section. It includes a search bar with the placeholder 'Search' and a magnifying glass icon. To the right of the search bar are several action buttons: 'Load full model list', 'Refresh Model', 'Train Model', 'Activate', 'Deactivate', and 'Delete'. Below these is a table with the following columns: 'Model-id', 'Description', 'Status', 'Total Records', 'Input Fields', and 'Output Fields'. The table contains one row with the following data: Model-id '59ddd967d1978b000b6d3b62', Description 'Training Sample data', Status 'ACTIVE', Total Records '20,000', Input Fields 'text', and Output Fields 'label'.

Below the 'Model List' section, there's a 'SINGLE PROPOSAL' section. It has a text input field with the placeholder 'text'. Below the input field is a button labeled 'Get Proposal'. To the right of the input field, there's a red-bordered box containing the 'Proposed Results'. The results are as follows:

- Proposed Results**
- Detected Language : English
- label : complaint
- Confidence Score : 88%
- Keywords used for proposal : it,My,track



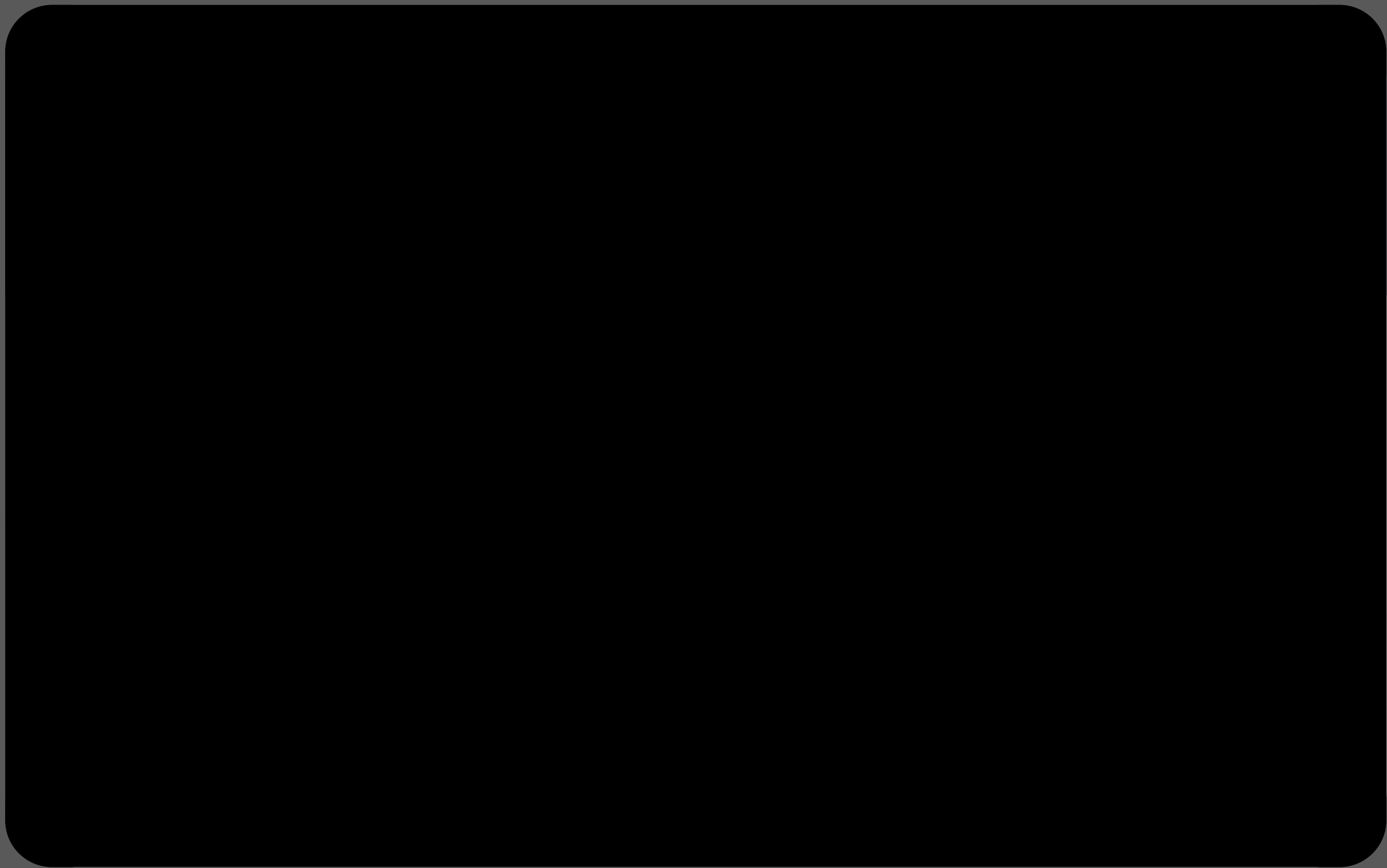
Jack Mayer

Bel-Air Customer



Jenny Smith

Service Agent





Jack Mayer

Bel-Air Customer



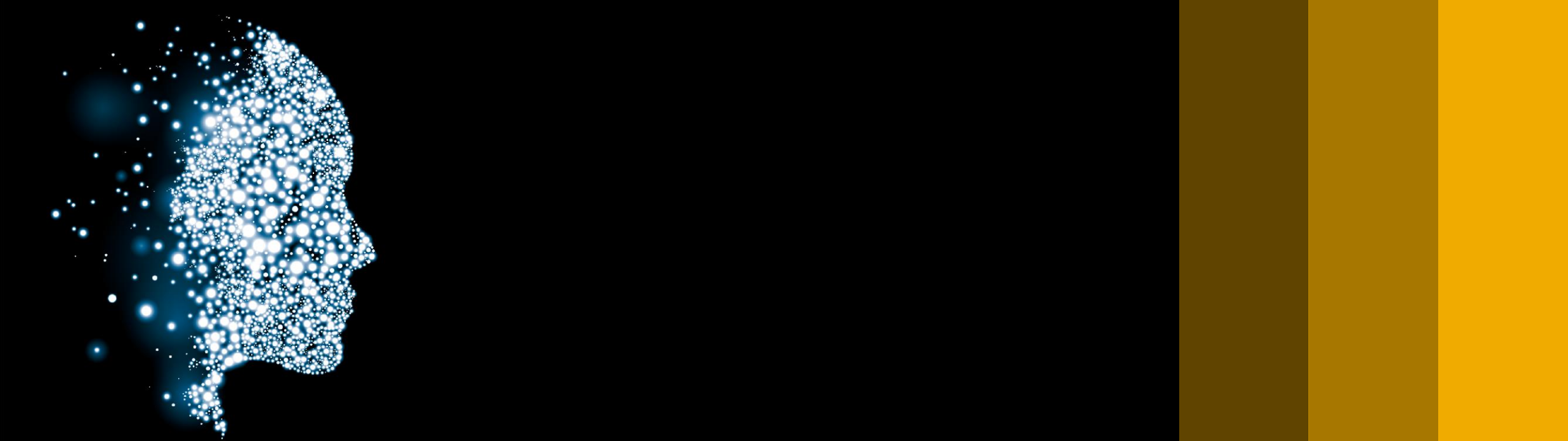
Jenny Smith

Service Agent

# Thank you.

**Contact information:**

**open@sap.com**



# Week 5: Industry Applications of Deep Learning

## **Unit 3: Machine Learning in Banking**

# Machine Learning in Banking

## Personalizing Chase's digital channels



```
{
  customer_id: 111,
  click_propensity_Ink: 0.78,
  click_propensity_Banking: 0.11
}
```



## 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

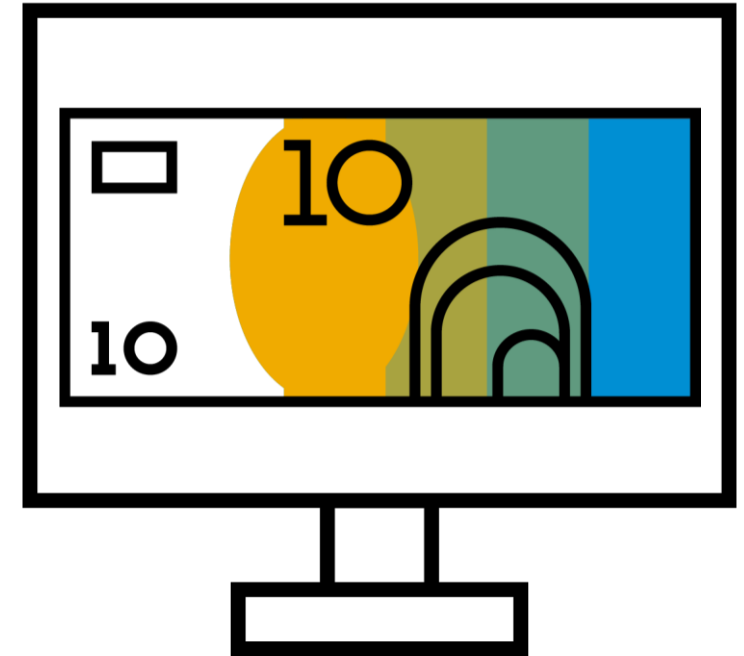


# Machine Learning in Banking

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

The screenshot displays the Chase Sapphire Preferred website interface. At the top, the navigation bar includes the 'SAPPHIRE PREFERRED' logo, 'Use Points', 'Earn Points', and a points balance of 113,928 PTS. The main banner features a poolside scene with lounge chairs and umbrellas, with the text 'Still looking for a hotel room?' and a 'Book Now' button. Below the banner, the 'Your points balance and recent activity' section shows the current balance of 113,928 PTS and the earning on the next statement of 1,517 PTS. To the right, the 'Points earned summary' table details earnings from dining, travel, and other sources.








Points earned summary	
Additional on Dining	Additional on Travel
4,221 PTS	6,358 PTS
1 Point Per \$1	45,042 PTS

# 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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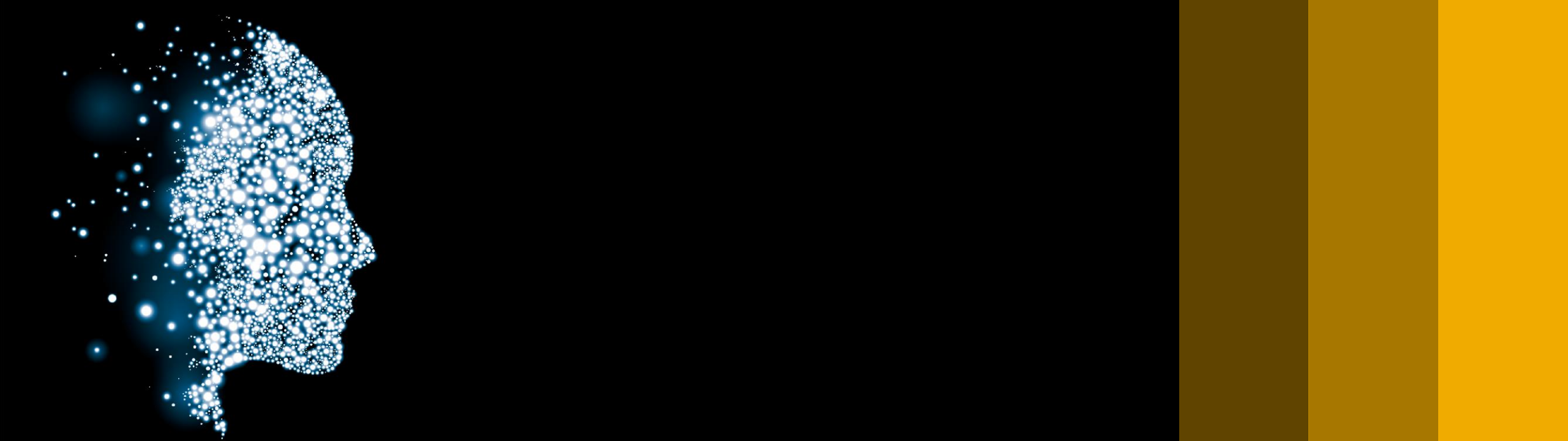
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Week 5: Industry Applications of Deep Learning

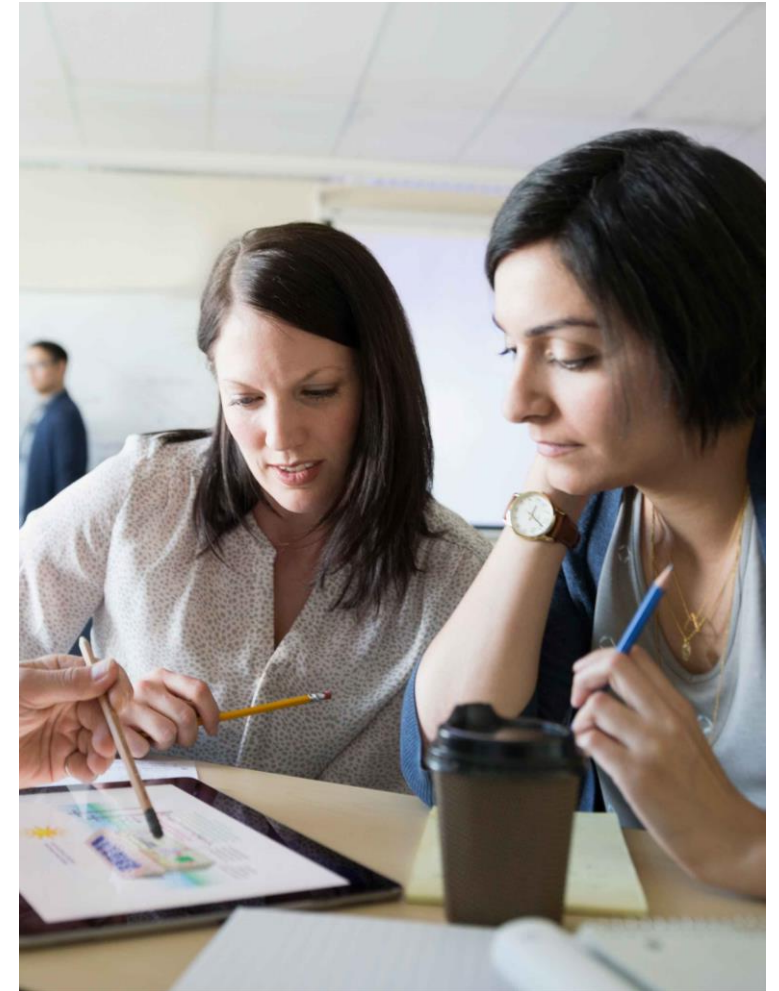
## **Unit 4: Medical Image Segmentation with Fully-Convolutional Networks**

# 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

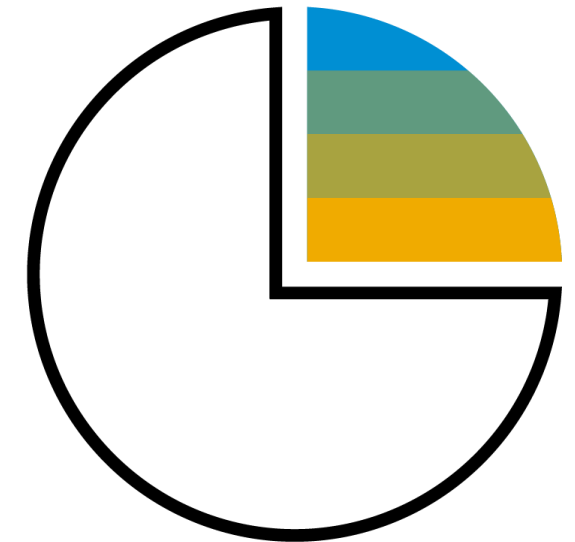
What is medical image segmentation?

## 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,...)



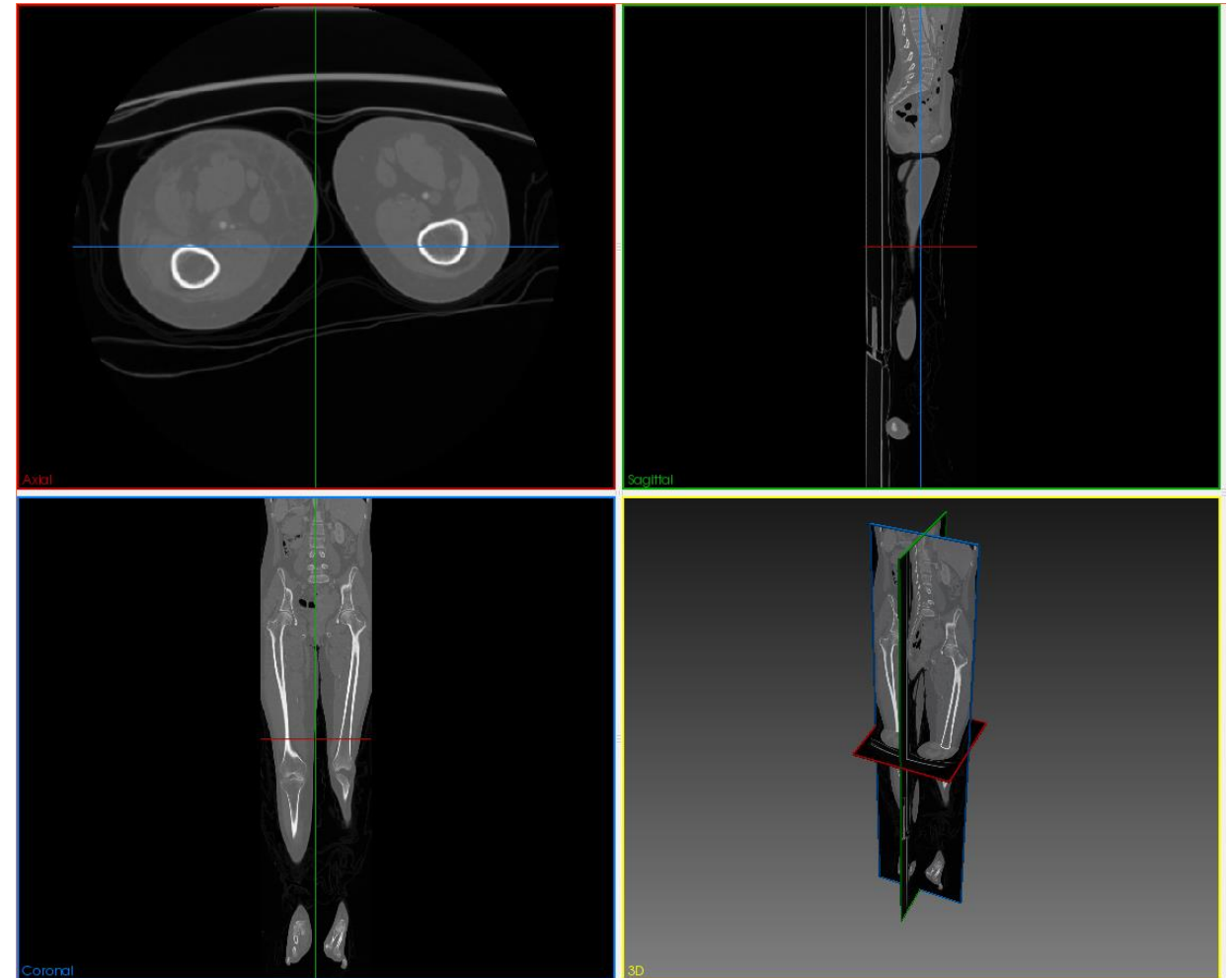
# Medical Image Segmentation with Fully-Convolutional Networks

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](https://simvascular.github.io)

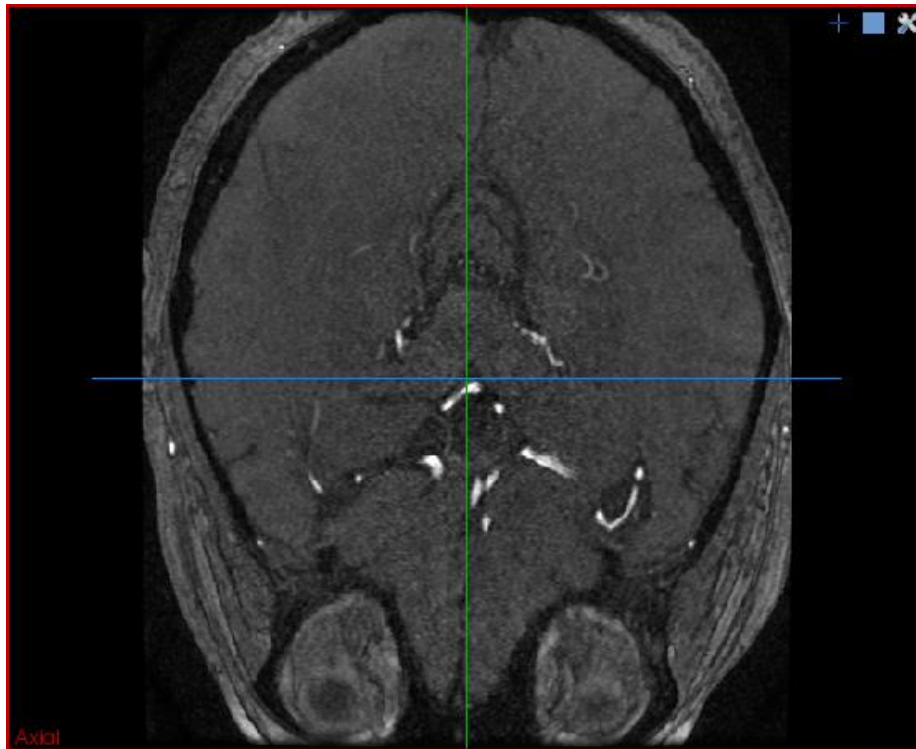


# Medical Image Segmentation with Fully-Convolutional Networks

What is medical image segmentation

## Medical Image Segmentation

- Exactly identify the region of interest by labeling all pixels



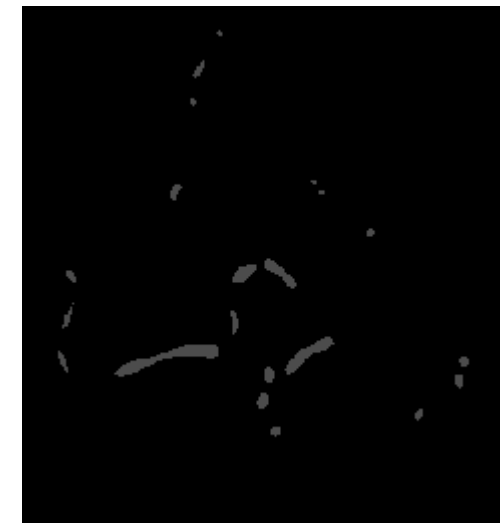
## Image Classification

Aneurysm/No Aneurysm?

## Image Segmentation

Pixel value 0 = Not blood vessel

Pixel value 1 = Blood vessel

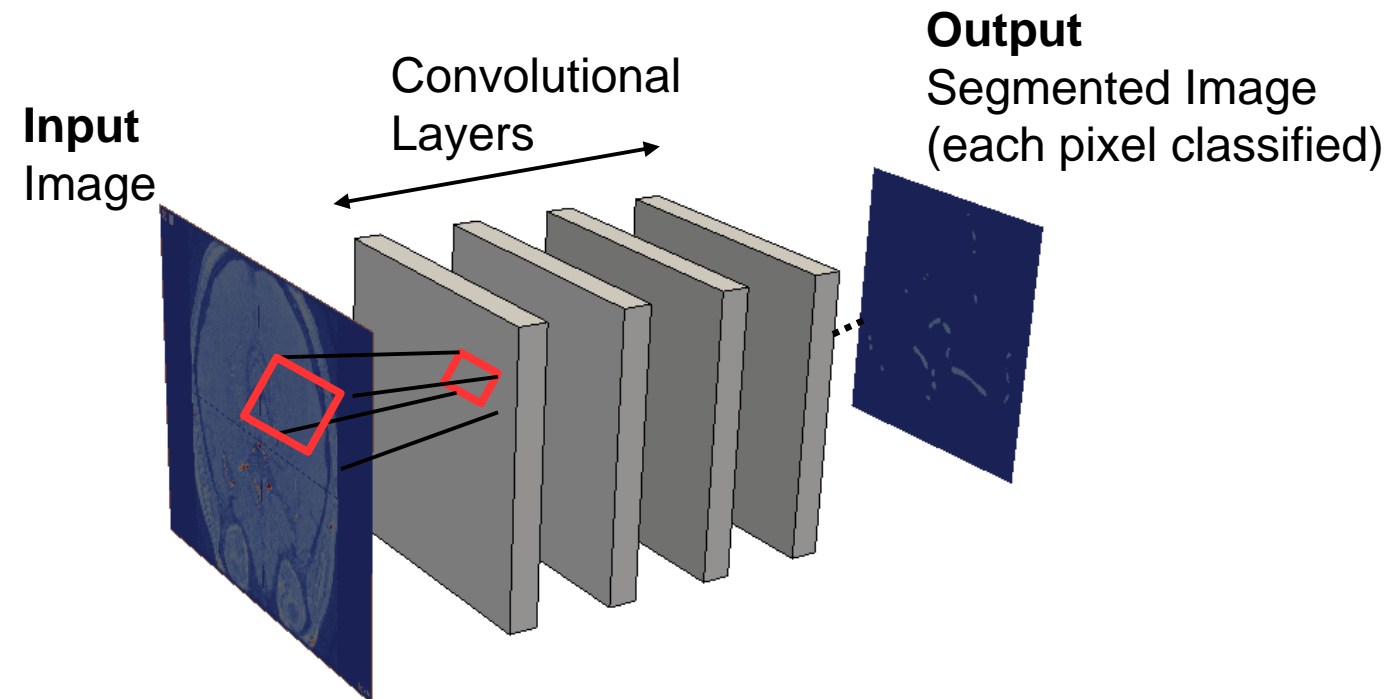


# Medical Image Segmentation with Fully-Convolutional Networks

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

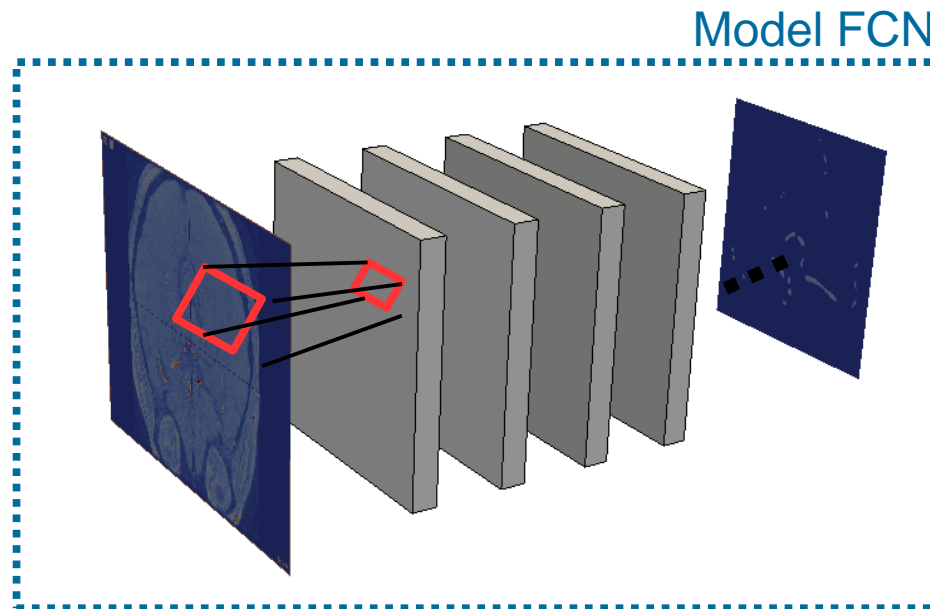


# Medical Image Segmentation with Fully-Convolutional Networks

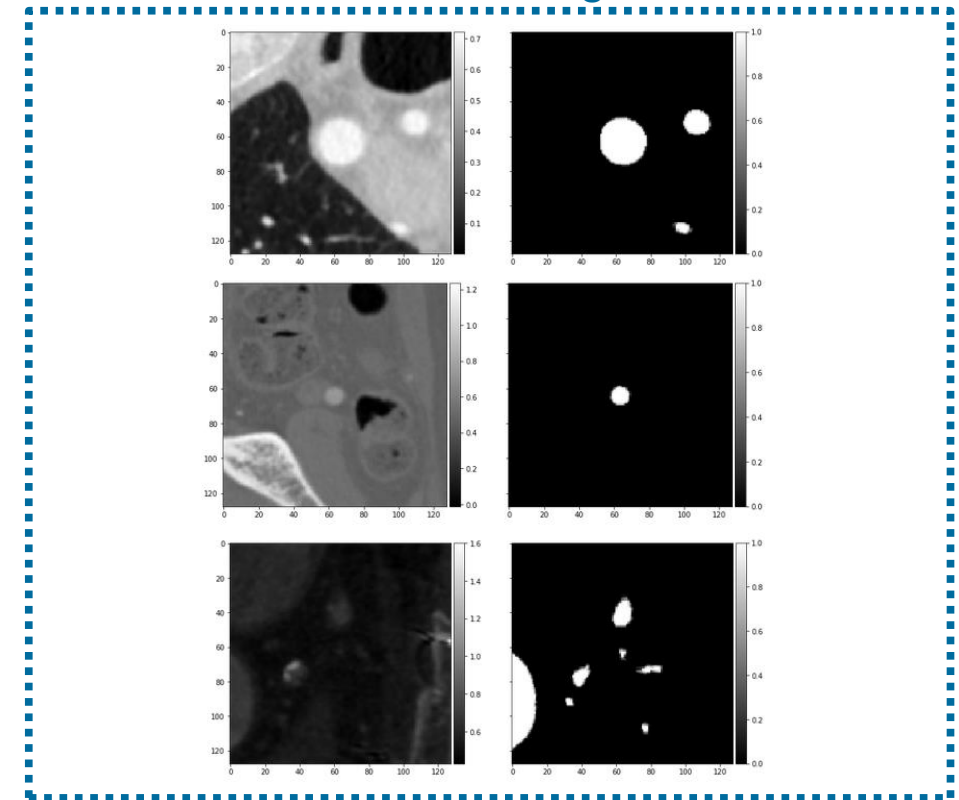
How do we use deep learning for medical image segmentation?

## 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



# Medical Image Segmentation with Fully-Convolutional Networks

Applied example

- Multimodal Brain Tumor Image Segmentation Benchmark



# Thank you.

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