



# ML meets Ad Creation – NLP und Bilderkennung für native Ads

Malte Pietsch – PAW '17

Problem

Solution

Learnings

# Problem domain: Native ads on news sites



**Das könnte Sie auch interessieren**

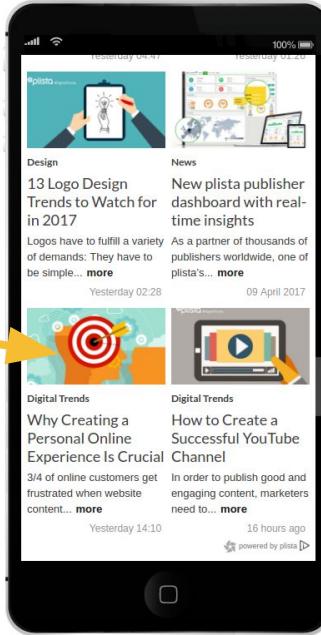
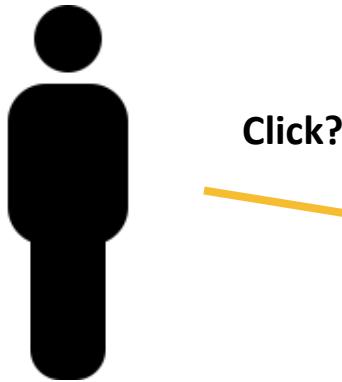
powered by plista ▶

<p><b>ANZEIGE</b> envia M Für ein warmes Zuhause.</p>	<p><b>ANZEIGE</b> Vodafone Websites mit Profi-Tools für Ärzte</p>	<p><b>ANZEIGE</b> BWT So wird Ihr Bad zur Wellness-Oase</p>
<p>Tatort aus Hannover Charlotte Lindholms Augenringe sind kaum mehr zu ertragen</p>	<p>Katalonien Puigdemont zwingt der EU sein Thema auf</p>	<p>Debatte um Seehofer Das Schauspiel der CSU beschädigt Jamaika</p>

## Key facts

- Widget below or beside article
- Recommendations for articles & ads
- > 3000 Publishers, worldwide
- Click-through-rate (CTR) = Clicks / Impressions

# How to improve ad performance?



## What drives a click?



User's context

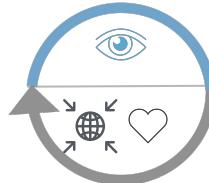


Personal interests



Appealing text & image

## Focus of this talk



Optimized Ads:  
Smart AdCreator

Optimized Delivery:  
Recommender System



**CLICK OR NO CLICK**

powered by  plista

# CLICK ⚡ NO CLICK

Round 1



## Treppenlifte 2015 - Preise und Kaufberatung

Treppenlifte aller Hersteller finden und vergleichen! ✓ neu ✓ gebraucht ✓ leasen ✓ mieten

**NO CLICK**

CTR

0.02 %



## Länger Zuhause wohnen bleiben?

Treppenliftlösung für nahezu jede Treppe finden. Jetzt kostenlos informieren!

**CLICK**

0.06 %

# CLICK ⚡ NO CLICK

Round 2

CTR



## Hamburg zeigt wie's geht: Arztpraxen werden digital

Weniger Papierkram. Mehr Zeit. 75% weniger Befundanfragen von Kollegen. Dokumente direkt vom Patienten-Smartphones übergeben - einfach mit LifeTime.

**CLICK**

0.20 %



## Hamburg zeigt wie's geht: Arztpraxen werden digital

Weniger Papierkram. Mehr Zeit. 75% weniger Befundanfragen von Kollegen. Dokumente direkt vom Patienten-Smartphones übergeben - einfach mit LifeTime.

**NO CLICK**

0.11 %

## Problem

## Solution

- Approach
- Model Selection
- Feature Engineering
- Deep dive: Image recognition
- Product: Smart AdCreator prototype

## Learnings

# Approach: Predict $\Delta CTR$ and provide actionable insights



- Historic data from 2014-2017 (~150k german ads)
- Train a model that ...
  - **predicts** the difference in CTR of similar ads
  - **explains** the prediction w.r.t features
  - **recommends** how to improve the ad

$$\frac{CTR_{ad} - \mu(CTR_{ad})}{\sigma(CTR_{allAds})}$$

Actionable insights



Predictive performance

# Model selection: It's a trade-off

White Box	Black box
<p><b>Models:</b> Variations of lin. regression</p> <p>⊖ Predict ⊕ Explain ⊕ Recommend</p>	<p><b>Models:</b> XGBoost, DNNs ...</p> <p>⊕ Predict ⊖ Explain ⊖ Recommend</p>

# Model selection: It's a trade-off

White Box	Black box (+heuristic)
<p><b>Models:</b> Variations of lin. regression</p> <p>⊖ Predict ⊕ Explain ⊕ Recommend</p>	<p><b>Models:</b> XGBoost, DNNs ... <b>Heuristics:</b> LIME, eli5 ...</p> <p>⊕ Predict ⊖ Explain ⊖ Recommend</p>

- Elastic Net for MVP
- Now: switching to XGBoost + Eli 5

# Feature engineering: Text, image and structured data



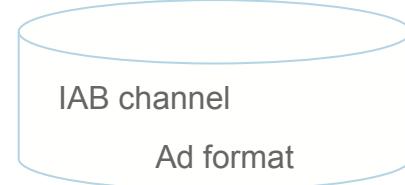
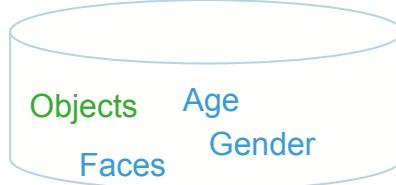
ABCDEFGHIJKLM  
NOPQRSTUVWXYZ



 Freeling  
 DBpedia Spotlight

 Retrained Inception v3  
 Kairos

 One-hot encoding



# Deep Dive: Customized multilabel image recognition



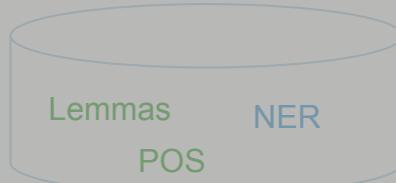
ABCDEFGHIJKLM  
NOPQRSTUVWXYZ



Freeling



DBpedia Spotlight



Retrained Inception v3

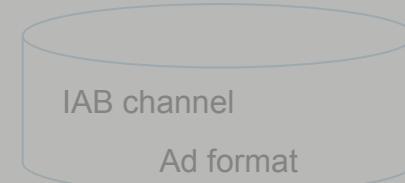


## Objects:

- $P(\text{bike}) = 0.85$
- $P(\text{sky}) = 0.79$
- $P(\text{rocks}) = 0.4$
- ....



One-hot encoding



# Deep Dive: Your choice



Option A: Convolution Basics



Option B: Inception module



# Deep Dive (A): Convolutional basics

1. Transform image to matrix

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

2. Define a filter (= feature detector)

1	0	1
0	1	0
1	0	1

3. Move filter over matrix and calculate dot product to get a feature map

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved  
Feature

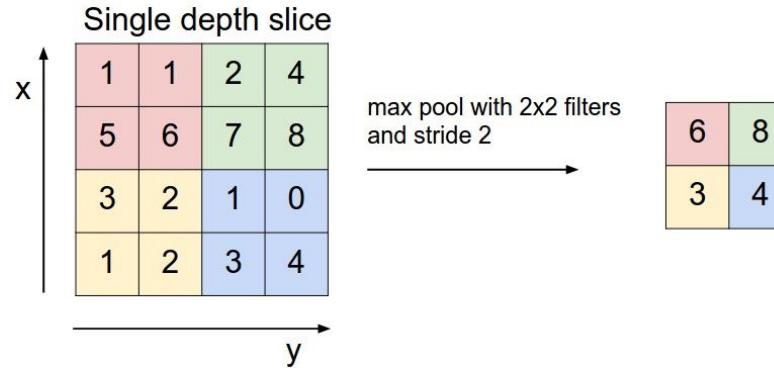


Sources:

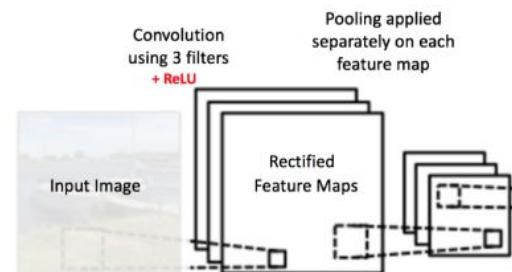
[http://deeplearning.stanford.edu/wiki/index.php/Feature\\_extraction\\_using\\_convolution](http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution)  
[http://cs.nyu.edu/~fergus/tutorials/deep\\_learning\\_cvpr12/](http://cs.nyu.edu/~fergus/tutorials/deep_learning_cvpr12/)

# Deep Dive (A): Convolutional basics

## 5. Apply Max Pooling to reduce dimensionality of feature map



## 6. Add multiple filters and train the weights

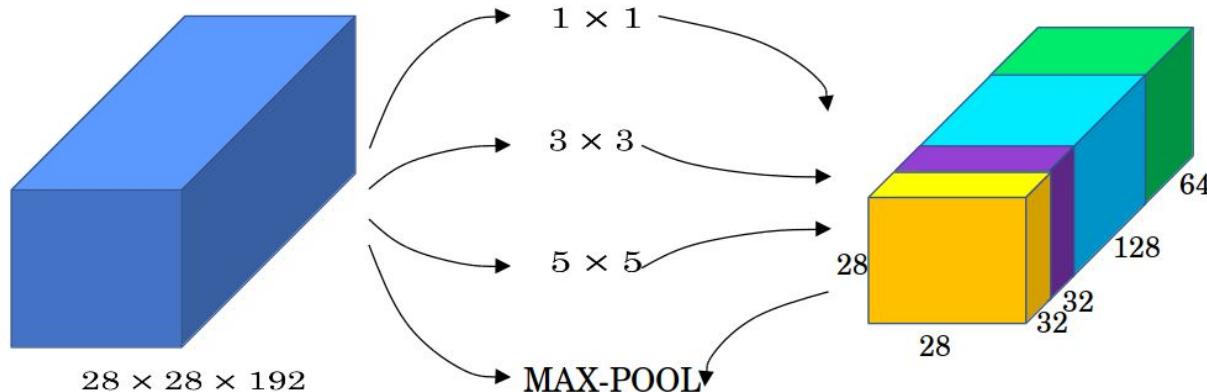


Sources:  
<http://cs231n.github.io/convolutional-networks/>  
<https://uijwalkarn.me/2016/08/11/intuitive-explanation-convnets/>

## Deep Dive (B): Inception Block

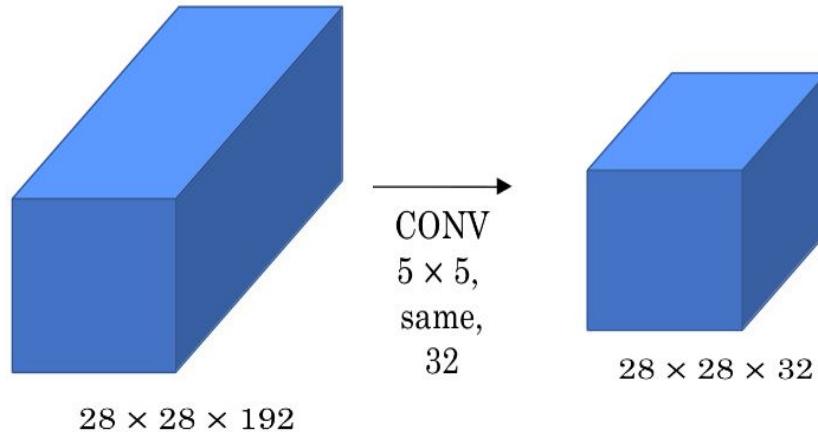
 **Problem** Which filter size shall we use in the CNN layers?

 **Idea** Apply different ones, concatenate results and let the model decide



## Deep Dive (B): Inception Block

 **Problem** Computational costs are exploding → **120 Mio. Multiplications**



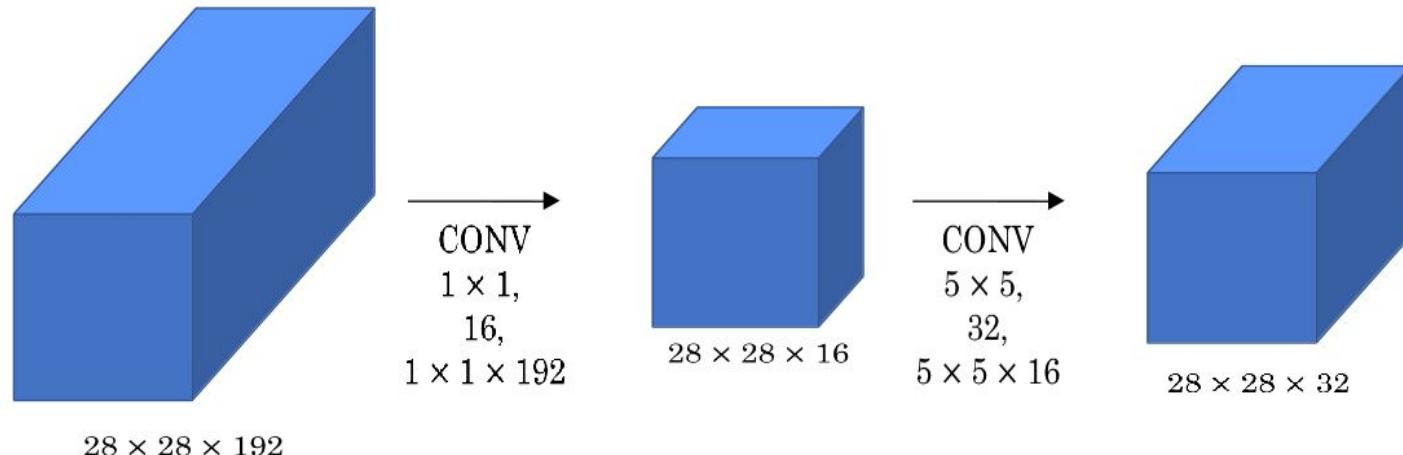
## Deep Dive (B): Inception Block



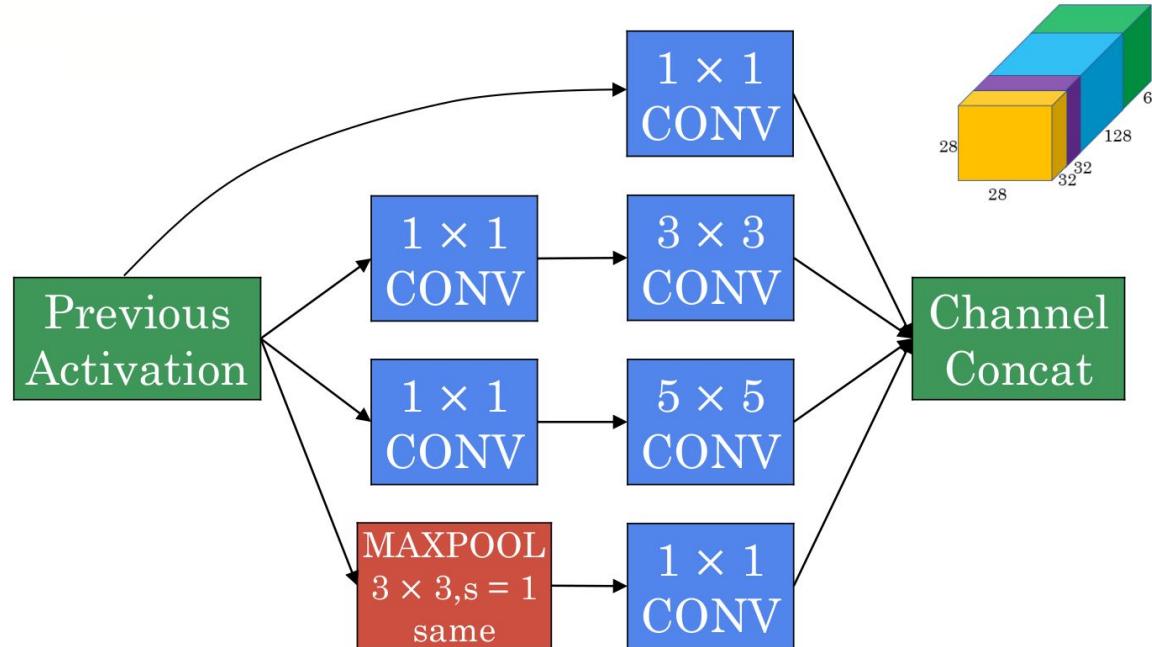
**Problem** Computational costs are exploding → **120 Mio. Multiplications**



**Idea** Reduce dimensionality via clever factorization of convolutions → **12.4 Mio. Multiplications**



## Deep Dive (B): Inception Block



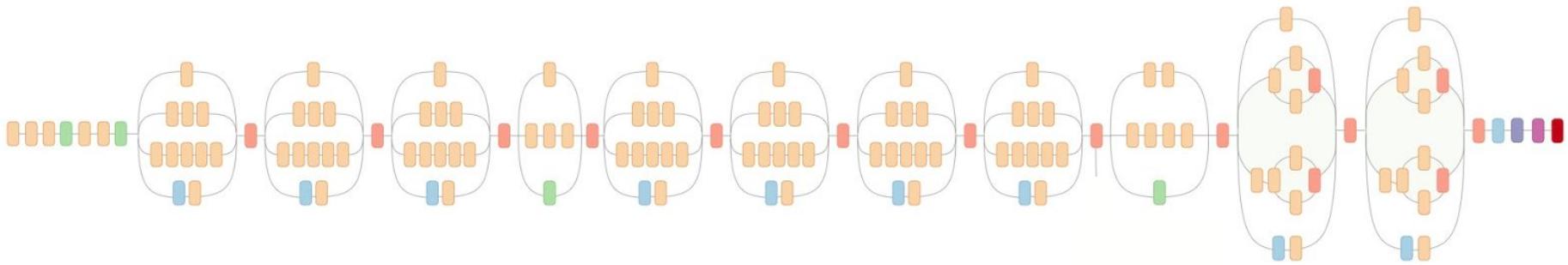
Source: Szegedy et al., 2015: "Going deeper with convolutions"

Figure from Coursera course "Convolutional Neural Networks" by Andrew Ng

# Deep dive: Transfer learning on Inception v3 Architecture



# Deep dive: Transfer learning on Inception v3 Architecture

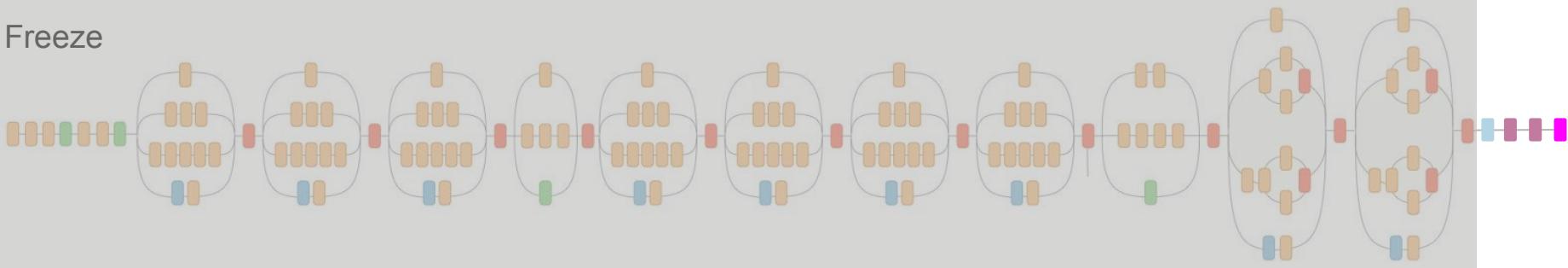


- Convolution
- AvgPool
- MaxPool
- Concat
- Dropout
- Fully connected
- Softmax
- Sigmoid

# Deep dive: Transfer learning on Inception v3 Architecture

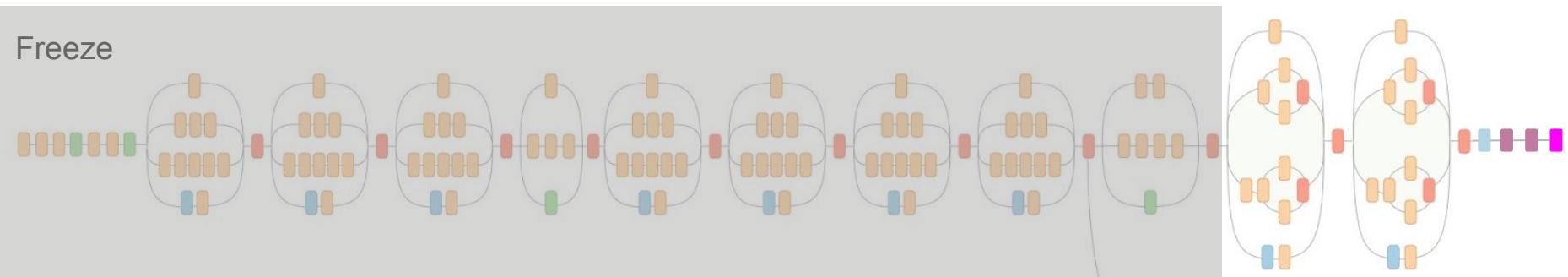


Freeze



- Orange: Convolution
- Blue: AvgPool
- Green: MaxPool
- Red: Concat
- Purple: Dropout
- Dark Red: Softmax
- Magenta: Sigmoid

# Deep dive: Transfer learning on Inception v3 Architecture



- Orange square: Convolution
- Light blue square: AvgPool
- Green square: MaxPool
- Red square: Concat
- Purple square: Dropout
- Magenta square: Fully connected
- Dark red square: Softmax
- Pink square: Sigmoid

# Deep dive: Transfer learning on Inception v3 Architecture



## Code Demo

The screenshot shows a Jupyter Notebook interface with the following details:

- Title:** Jupyter mga\_2017-11-06\_PAW\_talk\_object\_detection Last Checkpoint: 2 hours ago (autosaved)
- Toolbar:** File, Edit, View, Insert, Cell, Kernel, Help, CellToolbar
- Cell Status:** Found 0 images belonging to 0 classes.
- Section A: Train Inception**
  - A) Train top layers**
  - In [13]:** Python 3
  - Code:

```
# 1. load the pre-trained Inception V3 model (without top layers)
base_model = InceptionV3(weights='imagenet', include_top=False)

# 2. add custom top-layers for multilabel problem
x = base_model.output
x = GlobalAveragePooling2D(name='avg_pool')(x)
x = Dense(1024, activation='relu')(x)
predictions = Dense(num_classes, activation='sigmoid')(x)

# 3. combine to one model
model = Model(inputs=base_model.input, outputs=predictions)

# 4. we want to first train the top layers and keep the other weights frozen
for layer in base_model.layers:
    layer.trainable = False

# 5. compile the new model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['categorical_accuracy', 'top_k_categorical_accuracy'])

# 6. train model
best_path = "models/image/inception_fine_tune_large.h5"
best_model = callbacks.ModelCheckpoint(best_path, verbose=1, save_best_only=True)
model.fit_generator(train_generator, validation_data=val_generator, steps_per_epoch = train_steps,
                    epochs=epochs, class_weight = class_weights, callbacks=[best_model],
                    validation_steps=val_steps)

#7. save model
cur_date = datetime.date.today().strftime("%Y-%m-%d")
model.save('models/image/inception_fine_tune_%s.h5' % cur_date)
```
- B) Train deeper layers**

[https://github.com/tholor/paw\\_image\\_classification](https://github.com/tholor/paw_image_classification)

# Smart AdCreator



Total Score:



Title:

6 | Top | Rotweine | nur | 39,90 | €

Text:

Gratis | Versand | für | Rotwein-Freunde | - | Genießen | Sie | 6 | exklusive | Weine | aus | ganz | Europa | . | Jetzt  
bestellen | .

Entities:

Europa

Title & Text Score:



Grammatical Score:



Total Score:



Title:

6 Top Rotweine nur 39,90 €

Top: 2.46

Text: unglaublich: 2.6

einzigartig: 2.56

Gra traumhaft: 2.53

zwein-Freunde - Genießen Sie 6 exklusive Weine aus ganz Europa . Jetzt

erstklassig: 2.53

bes traum: 2.5

super: 2.5

Entitä himmlisch: 2.5

genial: 2.5

Euro toll: 2.48

Title & Text Score:



Grammatical Score:



# Smart AdCreator



Total Score:



Title:

6 Top Rotweine nur 39,90 €

Text:

Gratis Versand für Rotwein-Freunde - Genießen Sie 6 exklusive Weine aus ganz Europa . Jetzt bestellen .

Entities:

Europa

Place: 2.49

Location: 2.49

Title & Text Score:



Grammatical Score:



# Smart AdCreator - MVP



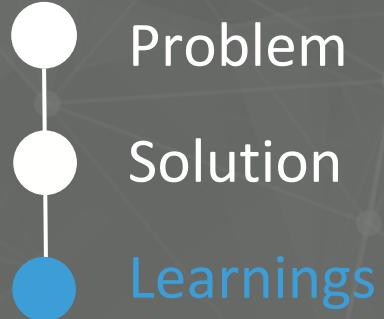
## Images

[http://www.plista.com/global/img/pets/upload/6e14810f3accd57f48acd62e47cdeba8\\_500x500x0x0.jpg](http://www.plista.com/global/img/pets/upload/6e14810f3accd57f48acd62e47cdeba8_500x500x0x0.jpg)

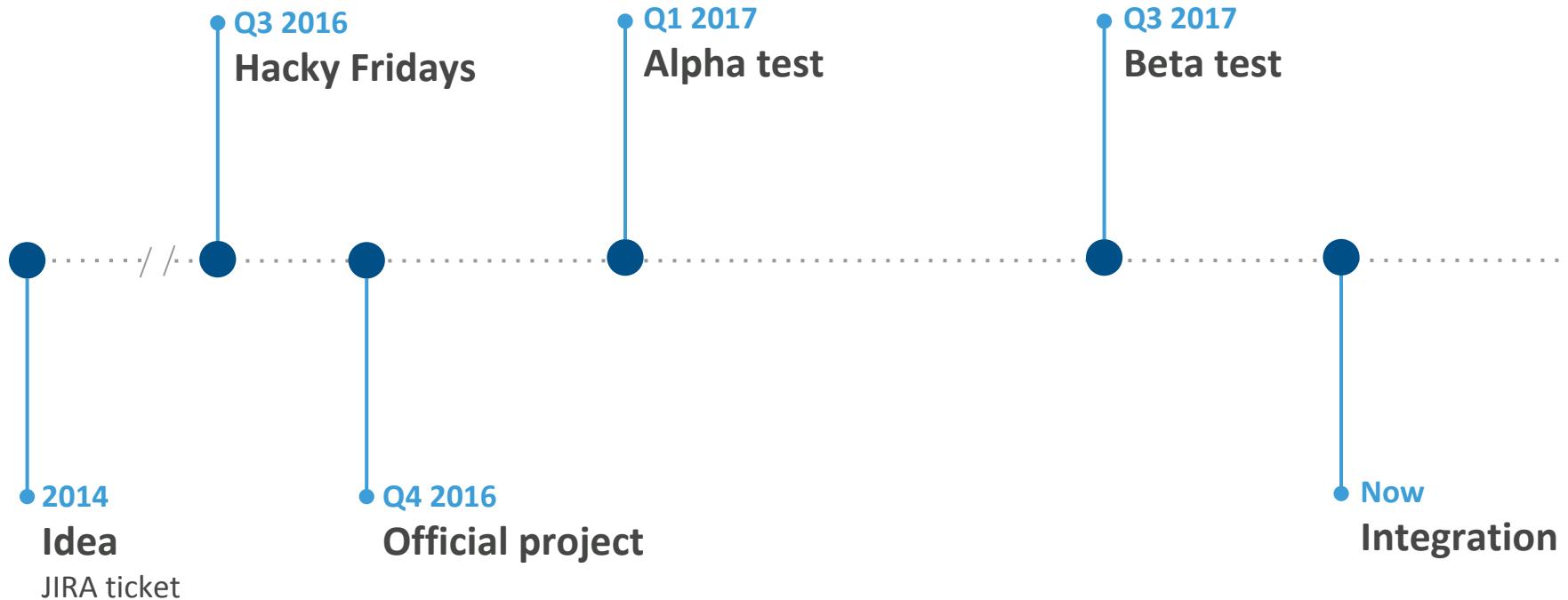


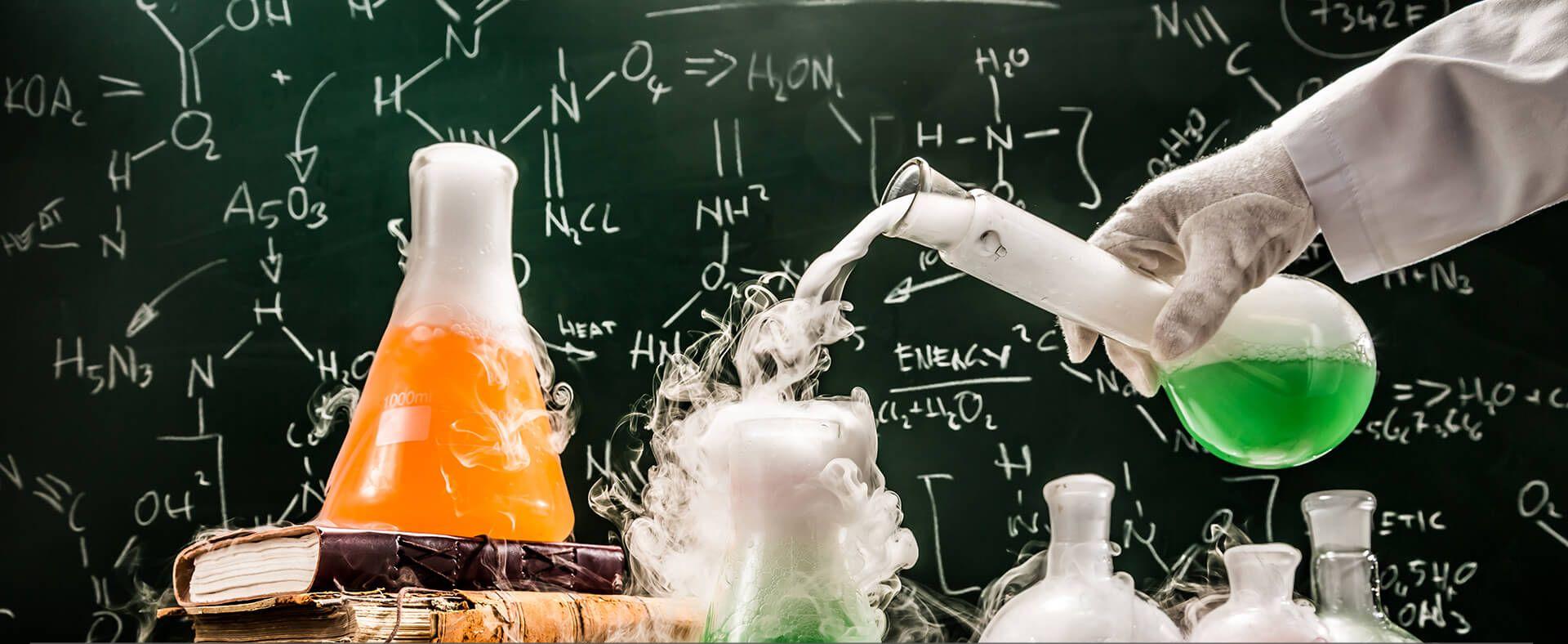
Image Score:





# Timeline





1. Dedicated time for experiments



## 2. Early involvement of users

A blurry, out-of-focus photograph of three business men in dark suits standing behind a large conference table. The table is covered with various documents, charts, and a laptop. In the foreground, there is a dark grey rectangular overlay containing the text.

### 3. Early commitment from management



4. Test & iterate fast, but don't compromise code quality



5. Usability first,  
model performance second

Thank you!  
Questions?