

# Introduction to Creating a Vision Solution in the Cloud

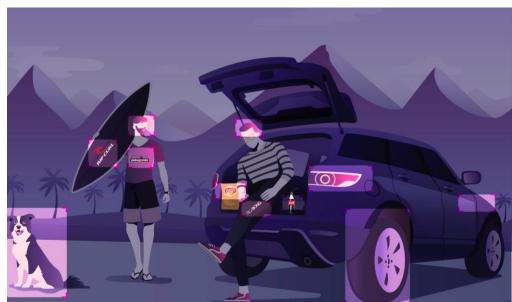


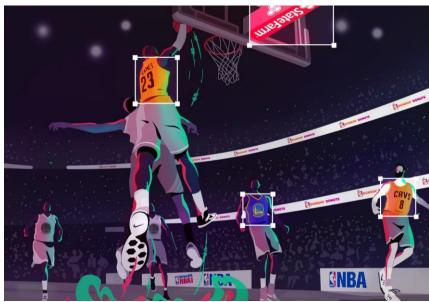
Nishita Sant, Computer Vision Scientist
May 2018

#### **GumGum Overview**



## GumGum is an artificial intelligence company with a particular focus in computer vision





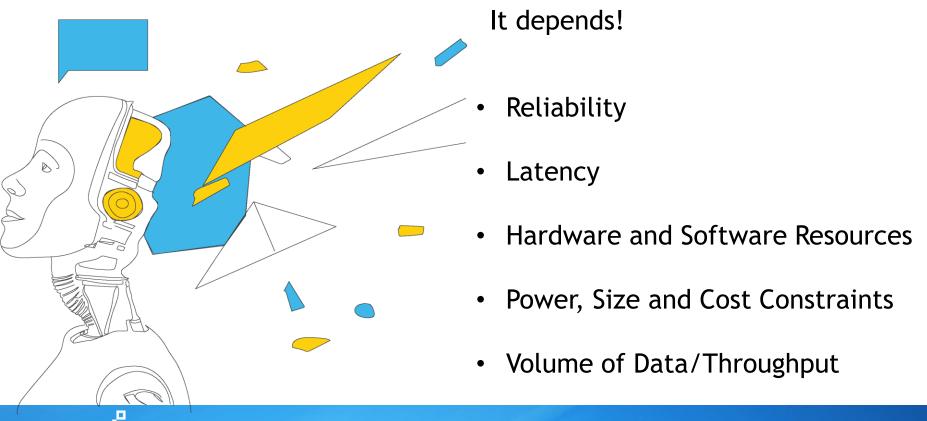
## Agenda



- 1. Why Computer Vision in the Cloud?
- 2. Performance Metrics
- 3. Computer Vision System Design
  - Computer Vision Modules, Features and API
  - Efficiency Studies (CPU vs GPU)

## Why Computer Vision in the Cloud?





## **Computer Vision System Design**



#### **Key Performance Indicators**













Recall

F1 Score

CPM

Throughput

Class Support

$$\left(\frac{TP}{TP+FP}\right)$$

$$(rac{TP}{TP+FN}$$

$$\left(rac{TP}{TP+FP}
ight) \qquad \left(rac{TP}{TP+FN}
ight) \qquad 2*\left(rac{Precision*Recall}{Precision+Recall}
ight) \qquad \left(rac{\$}{1000frames}
ight) \qquad \left(rac{frames}{sec}
ight) \qquad labels = [l_1, l_2, \ldots l_N]$$

$$\left(\frac{\$}{1000 frame}\right)$$

$$\left(rac{frames}{sec}
ight)$$

$$labels = [l_1, l_2, \dots l_N]$$

- **TP** True Positive
- **FP** False Positive
- **FN** False Negative

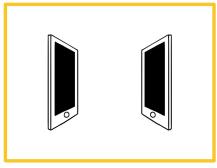
\*CPM - Cost Per Mille

## **Design Principles**





01 Scalability



03 (A)Synchronicity



02 Modularity/ Flexibility



04 Efficiency

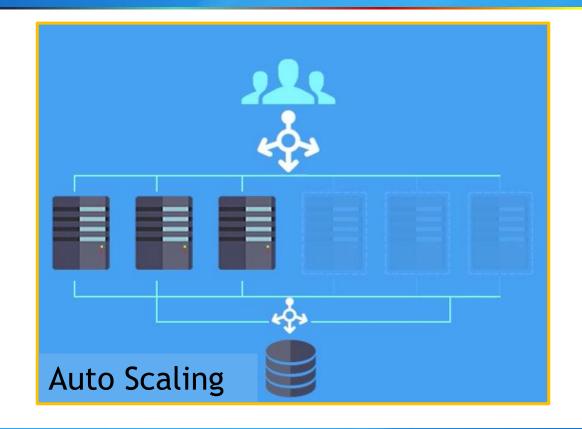
#### Design Principles - 01 Scalability





## Design Principles - 01 Scalability: How







#### Design Principles - 01 Scalability: Effect on metrics



Example: Logo Detection Engine



#### Estimate Acc.





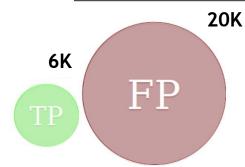
Recall = 60% FPR = 2%

#### Production

Throughput = 1M images/day
Estimated presence of logos = 1% = 10K images
Expected Recall = 0.6\*10K = 6K
Expected FPs = 0.02\*(1M-10K)

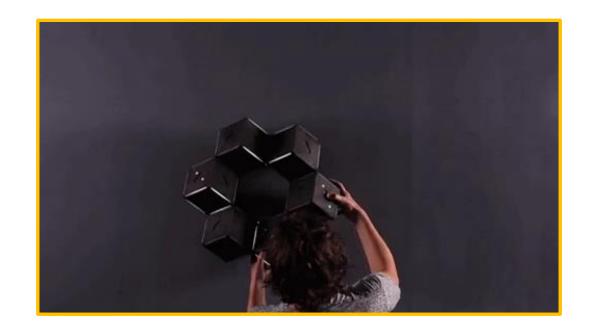
~ 20K

#### Realized Precision













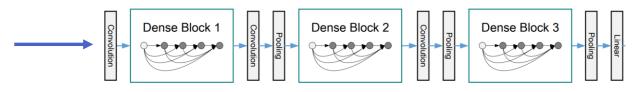
#### **Red Ford Mustang**



#### **Red-Ford-Mustang**



Not-Red-Ford-Mustang



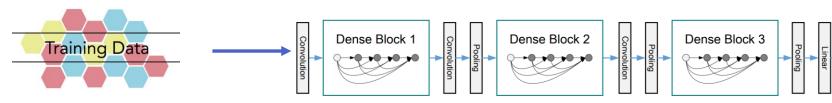
**DenseNet** 



Blue BMW Z4



Blue-BMW-Z4



Not-Blue-BMW-Z4

**DenseNet** 





## **Computer Vision Modules**



ML-based: CNNs, LSTMs, SVMs



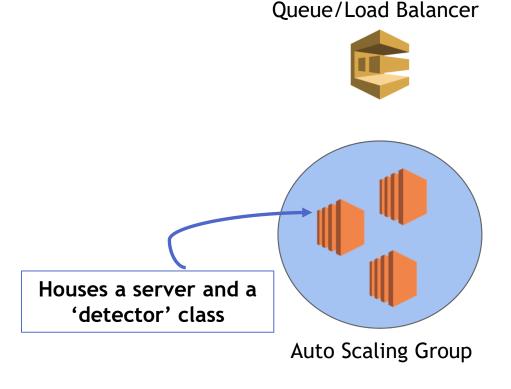
Traditional: Feature Matching



Hybrid: Feature Matching + SVM

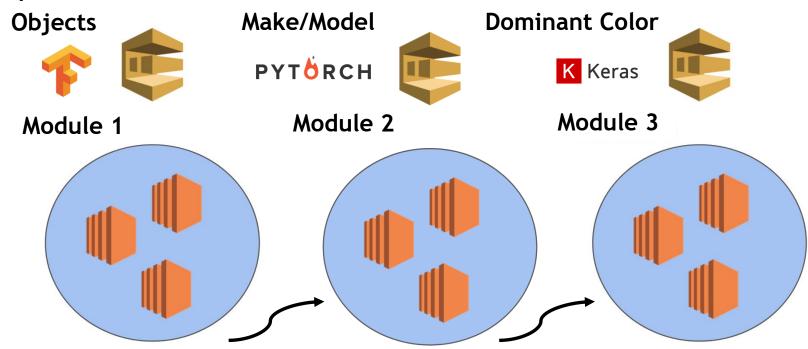


Heuristic: Design Logic





#### Computer Vision Features

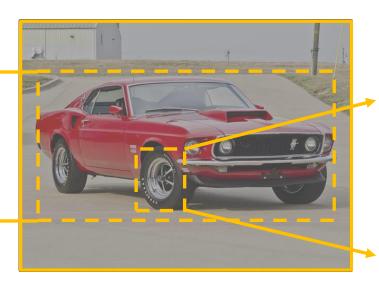




#### JSON for Inter-Process Communication

**Region:** List of points describing a contour

**Property:** Car



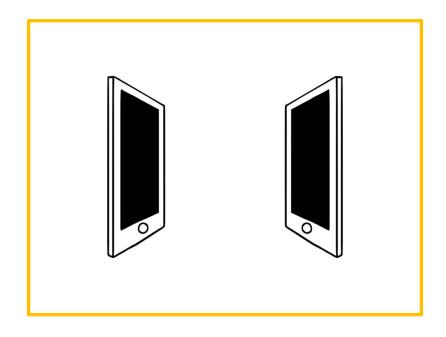
(Sub)Region: List of points describing a contour within another contour

**Property:** Tire, Black

Property: Car, Ford, Mustang, Red

## Design Principles - 03 (A)Synchronicity

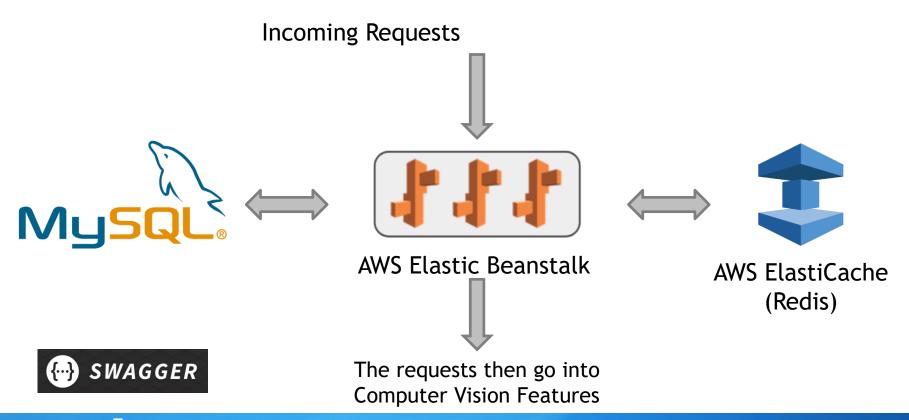






## Design Principles - 03 (A) Synchronicity





## Design Principles - 04 Efficiency



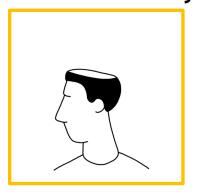


## Design Principles - 04 Efficiency



#### Hardware Efficiency

#### **RAM/GPU Memory**



Minimize memory footprint

#### Utilization



Maximize CPU/GPU utilization

## Design Principles - 04 Efficiency

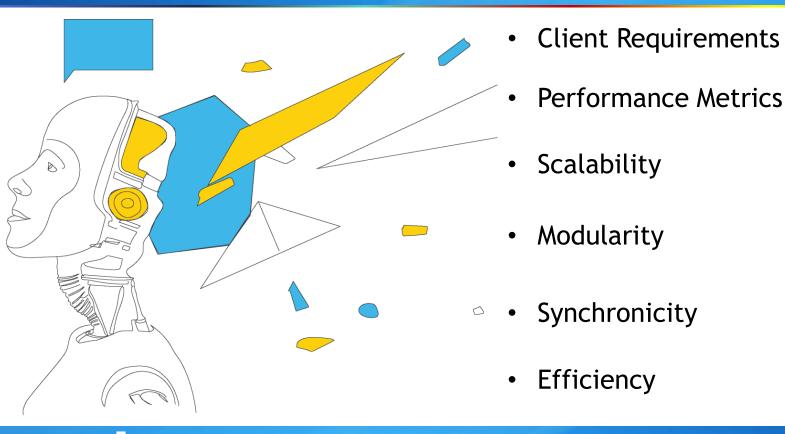


	CPU	GPU
COST	Detector: \$1.63 CPM	Detector: \$0.0829 CPM
	Classifier: \$0.124 CPM	Classifier: \$0.0338 CPM
RUNTIME	Detector: 14.59 sec/image	Detector: 0.4596 sec/image
	Classifier: 1.11 sec/image	Classifier: 0.1873 sec/image

<sup>\*</sup> CPM = Cost Per Mille

## **Key Takeaways**





#### Thank You





#### Resources



- Computer Vision: At the Edge or In the Cloud? It Depends.
- Keras Wiki, Keras Documentation, Github Keras
- MXNet
- PyTorch
- Open Neural Network Exchange
- Caffe2
- TensorFlow
- Swapper API Development Tool
- Amazon ElasticSearch
- Amazon ElasticBeanstalk
- Spring Framework for Java Platform
- Densly Connected Convolutional Networks
- Three reasons why apache avro data serialization is a good choice
- Apache Avro Schema 1.8.1

#### **About GumGum**







70%
Of Fortune 100
Companies





#### **Computer Vision Applications**

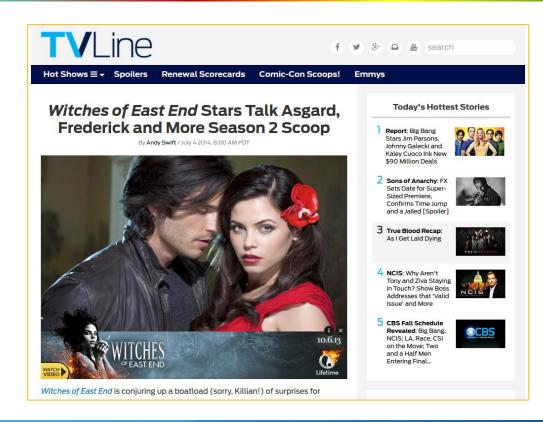


#### ...in Augmented Advertising

#### **CONTENT ENHANCES AD**

Ad creative built to incorporate image content

Localized detection of objects, people, or body parts using Computer Vision



## **Sports Sponsorship Measurement**

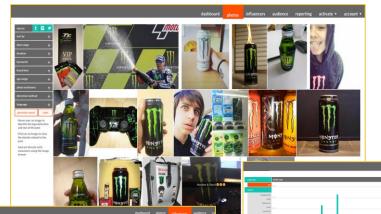






#### **Social Listening**





61.4K

#### **GUMGUM SOCIAL**

Ingest social posts with visual content from firehose of Twitter, Instagram, etc.

Detect presence and location of brand logos or other objects

Analytics dashboard, interact with influencers





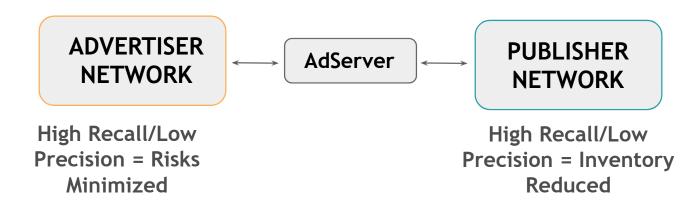
## **Design Principles**



#### **ACCURACY SPECS CAN BE CASE SPECIFIC**

Example: Brand Safety in Digital Advertising







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#### Inter-Process Communication

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```

#### **Inter-Process Communication**

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