Practical Deep learning for Computer Vision

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Warning

Deep learning is new SEXY (for a reason!)

Week 3: Object Recognition

- Resnet from scratch
- Transfer Learning
- Google Colab

Week 4: Object Detection

- DarkNet & YOLO
- Transfer Learning

Week 5: GAN

- AWS
- GANs

Week 5. AWS - GAN

- Cloud computing
- Cloud service providers
  - AWS: Amazon Web Services
  - Google Cloud
  - Microsoft Azure
  - IBM Cloud

Amazon Web Services (AWS)

Enable businesses and developers to use web services to build scalable, sophisticated applications.

amazon web services

Six Advantages & Benefits of AWS Cloud Computing

Trade capital expense for variable expense.

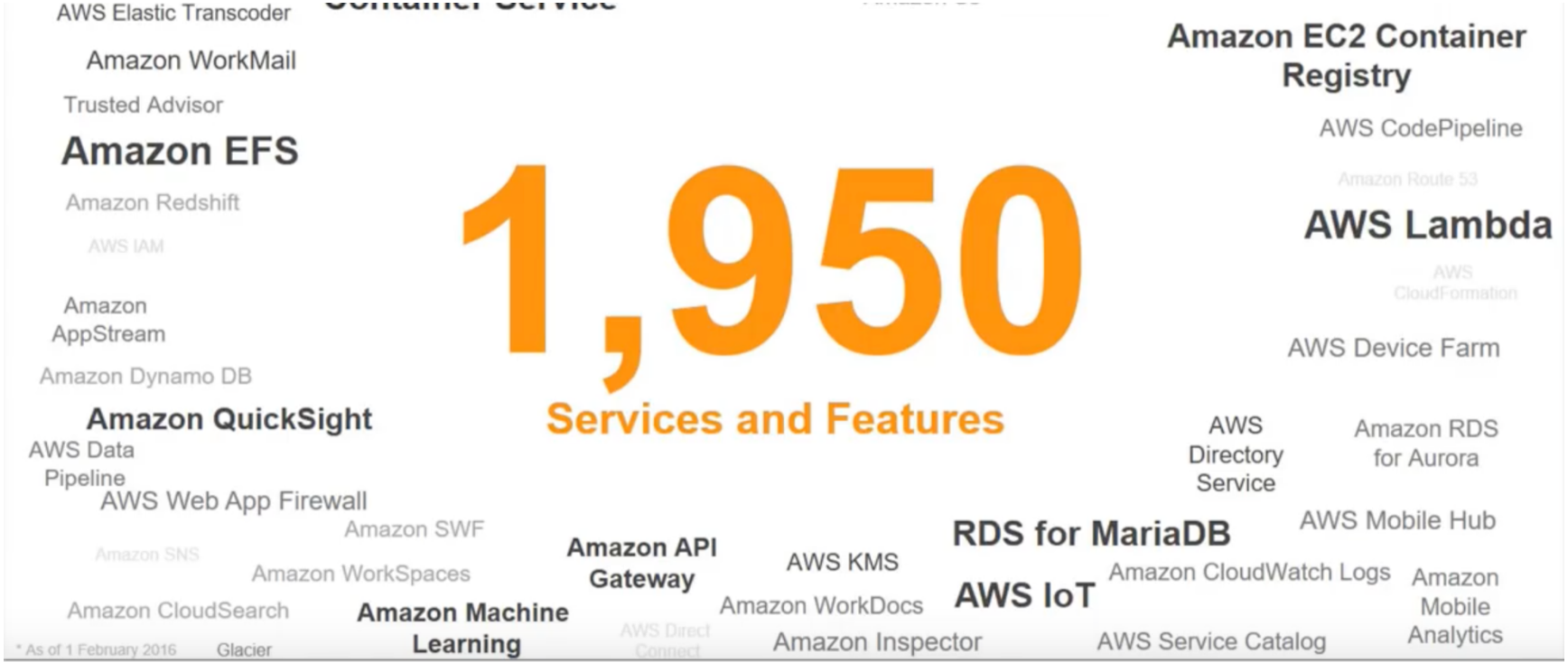
Increase speed and agility.

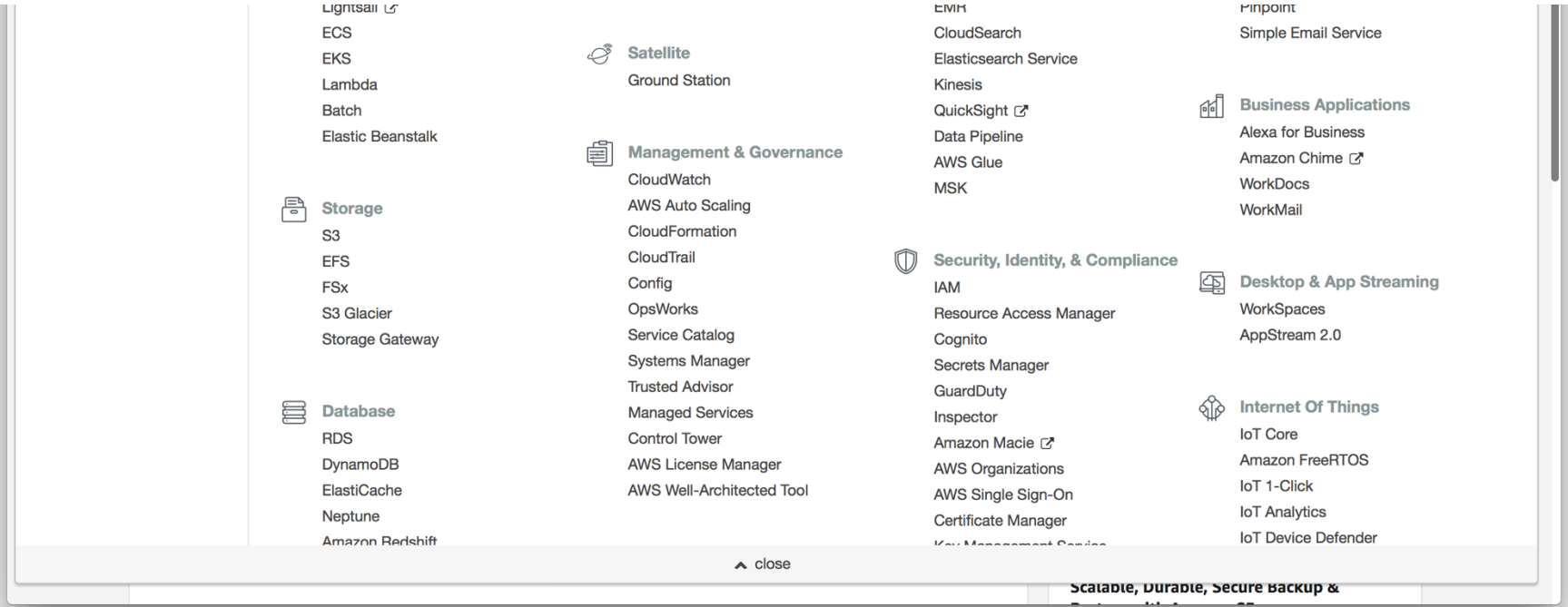
Benefit from massive economies of scale.

Stop spending money on running and maintaining data centers.

Stop guessing capacity.

Go global in minutes.


AWS Elastic Transcoder
Amazon WorkMail
Trusted Advisor
Amazon EFS
Amazon Redshift
AWS IAM
Amazon AppStream
Amazon Dynamo DB
Amazon QuickSight
AWS Data Pipeline
AWS Web App Firewall
Amazon SNS
Amazon SWF
Amazon WorkSpaces
Amazon CloudSearch
Amazon Machine Learning
Glacier
* As of 1 February 2016
1,950
Services and Features
Amazon EC2 Container Registry
AWS CodePipeline
Amazon Route 53
AWS Lambda
AWS CloudFormation
AWS Device Farm
AWS Directory Service
Amazon RDS for Aurora
AWS Mobile Hub
RDS for MariaDB
Amazon API Gateway
AWS KMS
AWS IoT
Amazon CloudWatch Logs
Amazon Mobile Analytics
Amazon WorkDocs
AWS Direct Connect
Amazon Inspector
AWS Service Catalog


Lightsail
ECS
EKS
Lambda
Batch
Elastic Beanstalk
Storage
S3
EFS
FSx
S3 Glacier
Storage Gateway
Database
RDS
DynamoDB
ElastiCache
Neptune
Amazon Redshift
Satellite
Ground Station
Management & Governance
CloudWatch
AWS Auto Scaling
CloudFormation
CloudTrail
Config
OpsWorks
Service Catalog
Systems Manager
Trusted Advisor
Managed Services
Control Tower
AWS License Manager
AWS Well-Architected Tool
EMR
CloudSearch
Elasticsearch Service
Kinesis
QuickSight
Data Pipeline
AWS Glue
MSK
Security, Identity, & Compliance
IAM
Resource Access Manager
Cognito
Secrets Manager
GuardDuty
Inspector
Amazon Macie
AWS Organizations
AWS Single Sign-On
Certificate Manager
Pinpoint
Simple Email Service
Business Applications
Alexa for Business
Amazon Chime
WorkDocs
WorkMail
Desktop & App Streaming
WorkSpaces
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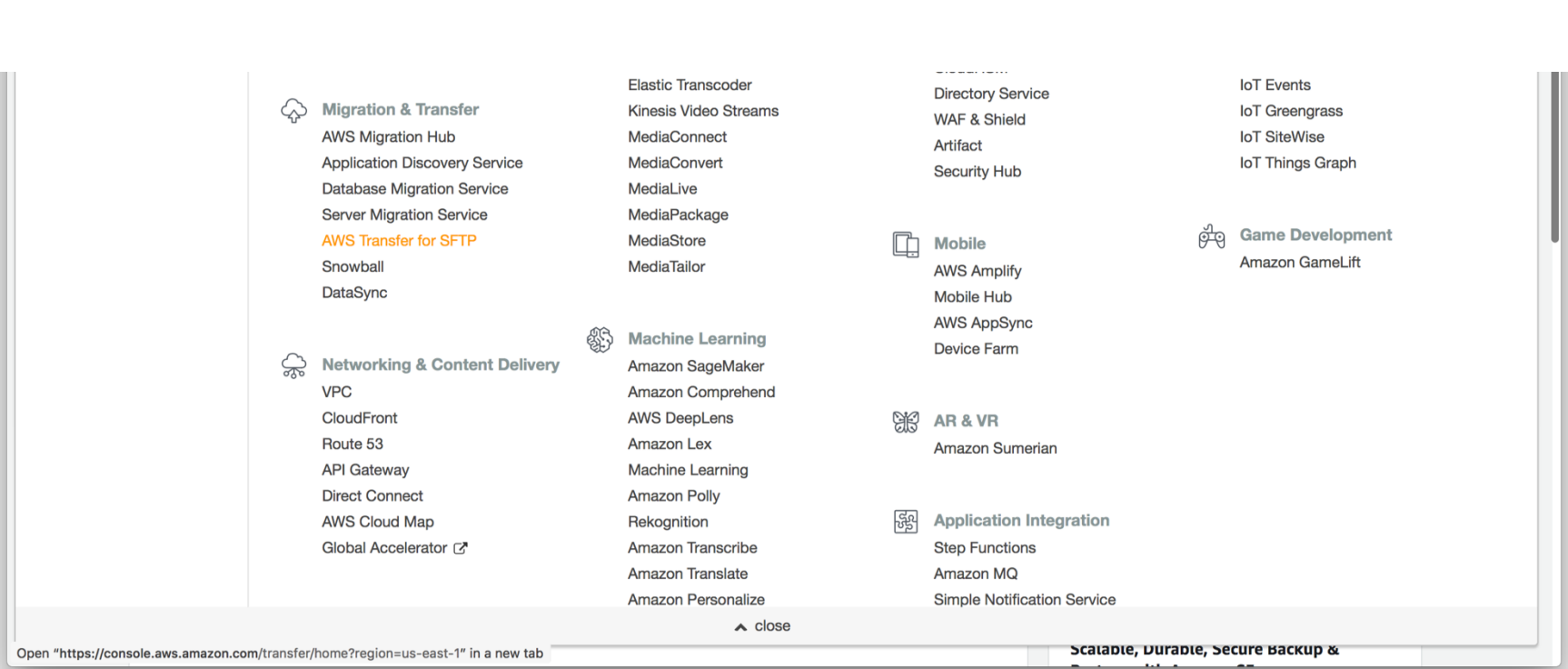
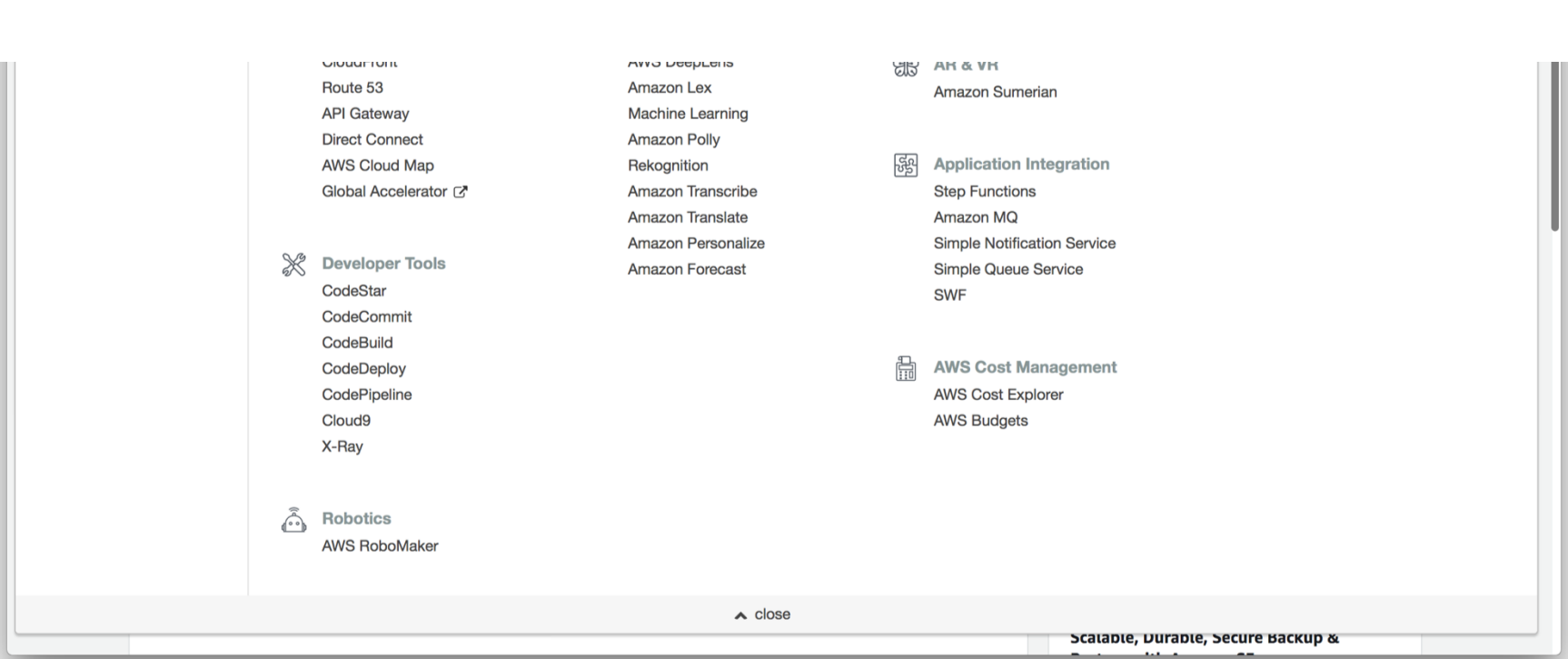
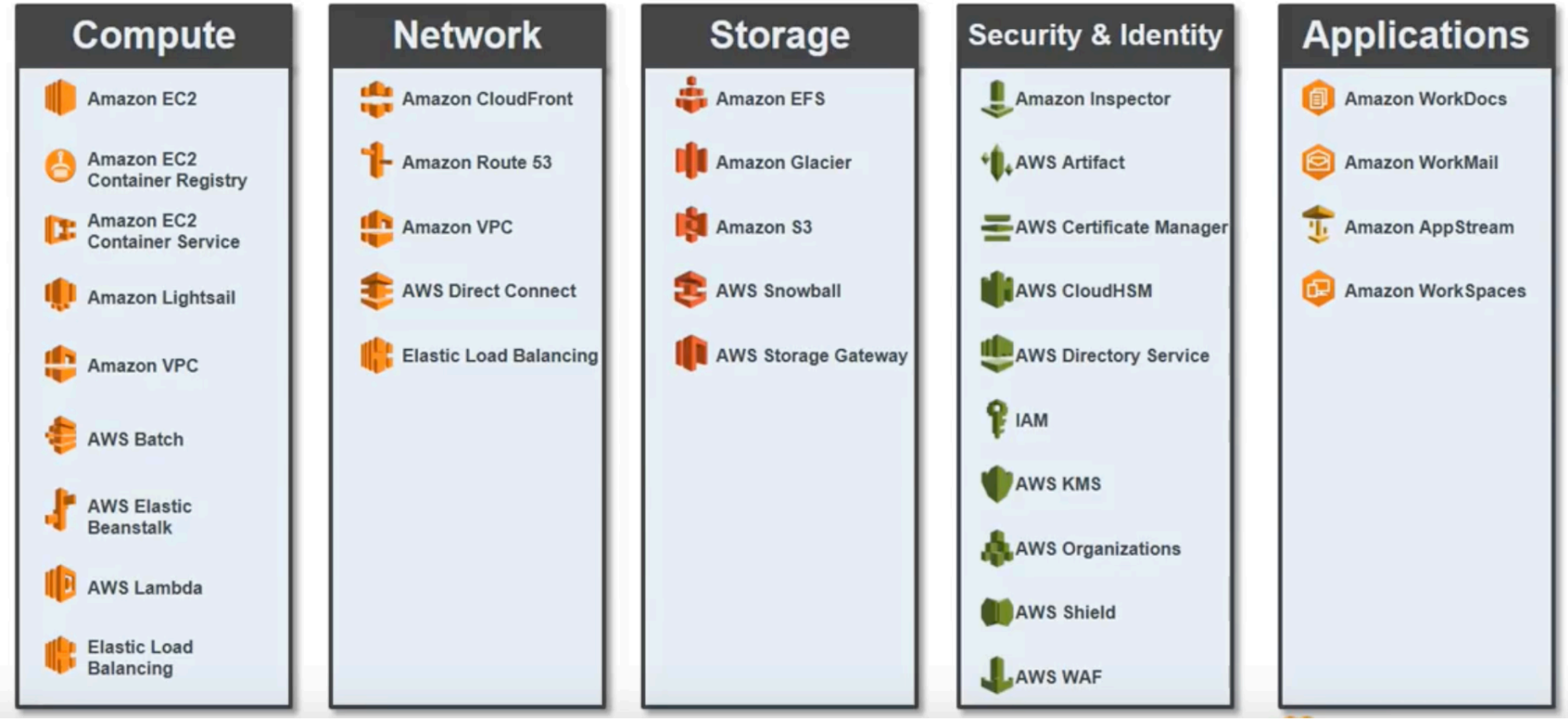
Internet Of Things
IoT Core
Amazon FreeRTOS
IoT 1-Click
IoT Analytics
IoT Device Defender
close
Scalable, Durable, Secure Backup &


Migration & Transfer
AWS Migration Hub
Application Discovery Service
Database Migration Service
Server Migration Service
AWS Transfer for SFTP
Snowball
DataSync
Networking & Content Delivery
VPC
CloudFront
Route 53
API Gateway
Direct Connect
AWS Cloud Map
Global Accelerator
Elastic Transcoder
Kinesis Video Streams
MediaConnect
MediaConvert
MediaLive
MediaPackage
MediaStore
MediaTailor
Machine Learning
Amazon SageMaker
Amazon Comprehend
AWS DeepLens
Amazon Lex
Machine Learning
Amazon Polly
Rekognition
Amazon Transcribe
Amazon Translate
Amazon Personalize
Directory Service
WAF & Shield
Artifact
Security Hub
Mobile
AWS Amplify
Mobile Hub
AWS AppSync
Device Farm
AR & VR
Amazon Sumerian
Application Integration
Step Functions
Amazon MQ
Simple Notification Service
IoT Events
IoT Greengrass
IoT SiteWise
IoT Things Graph
Game Development
Amazon GameLift
close
Open "https://console.aws.amazon.com/transfer/home?region=us-east-1" in a new tab
Scalable, Durable, Secure Backup &

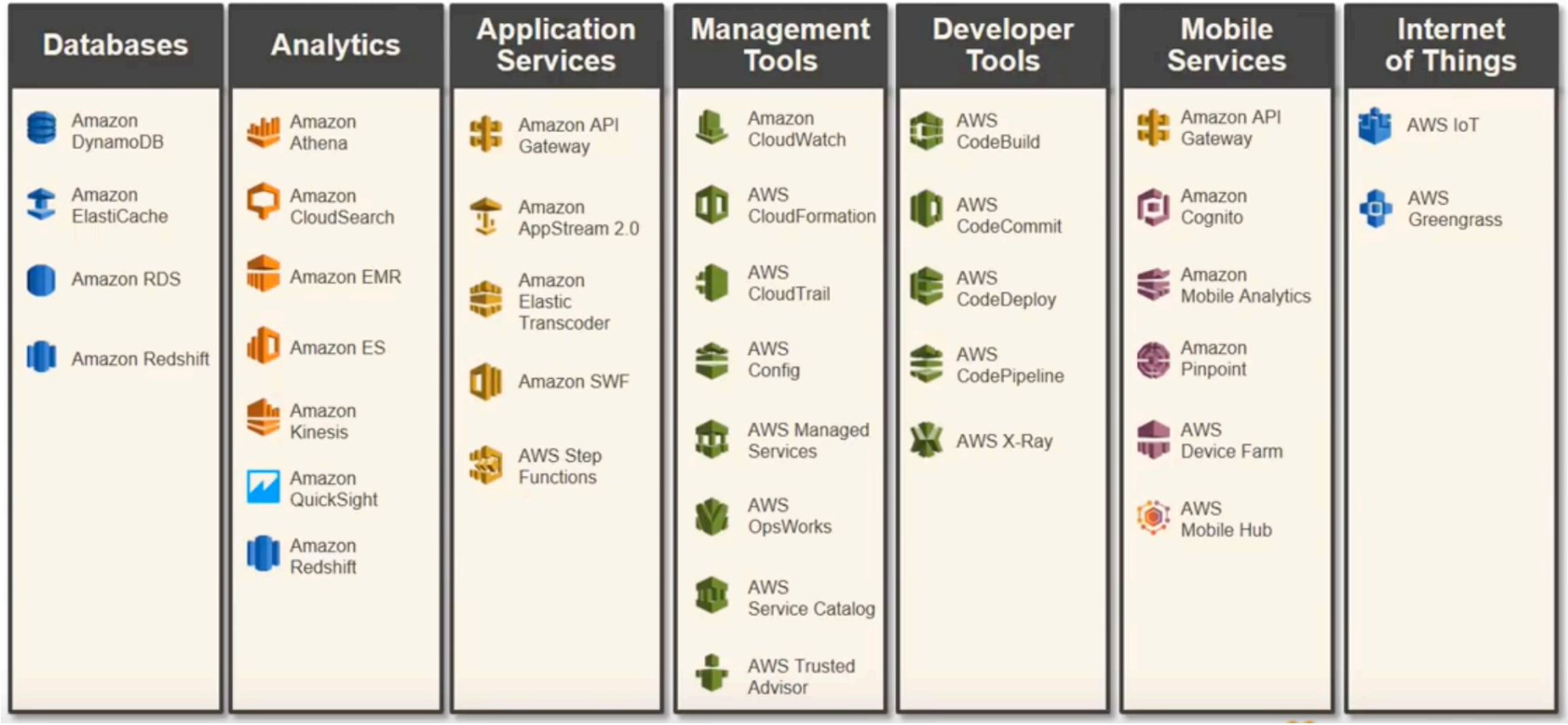


https://www.youtube.com/watch?v=TkT4iFRkaZk

AWS Foundation Services



AWS Platform Services



https://www.youtube.com/watch?v=K3qbY8j_Qfs&t=774s

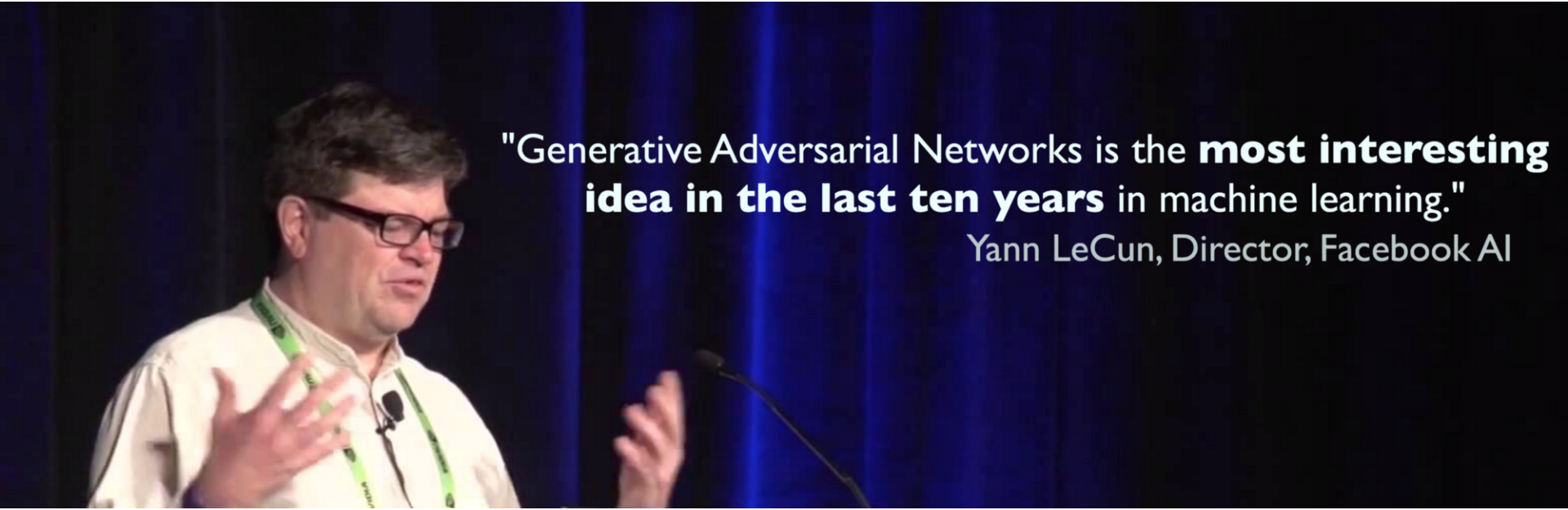
Deep learning on AWS

- https://aws.amazon.com/deep-learning/

Computer Vision on AWS

- https://aws.amazon.com/computer-vision/

Generative Adversarial Models - Why?



- Very cool applications

Create Anime characters

Towards the automatic Anime characters creation with Generative Adversarial Networks

Pose-guided Person Image Generation

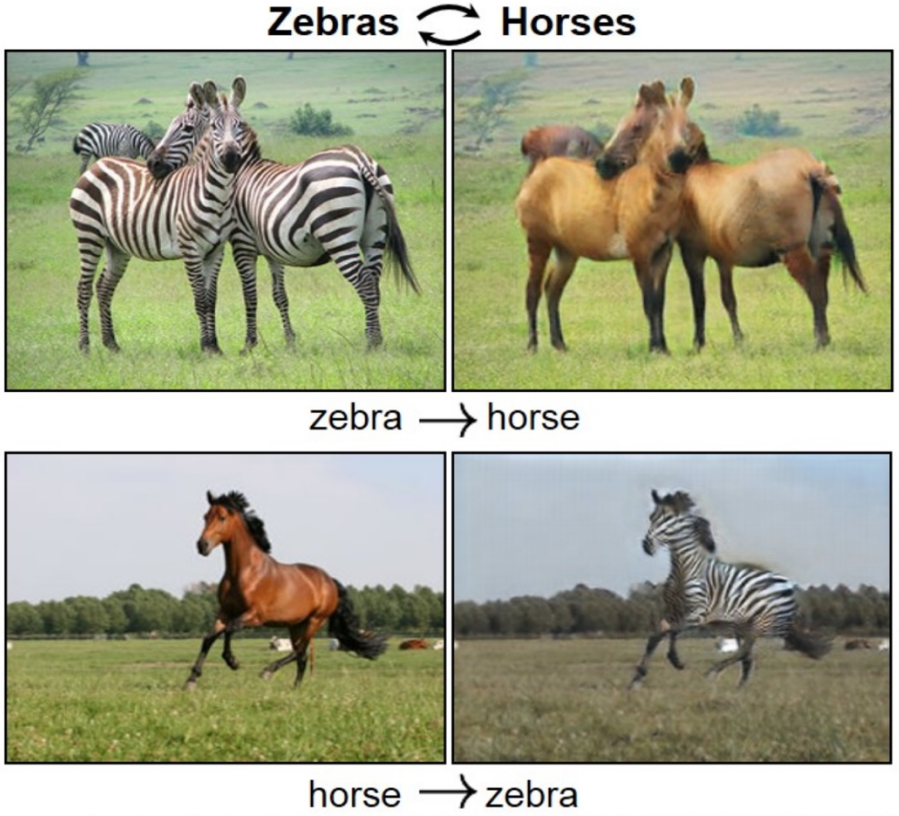
Ground truth

Generated

https://papers.nips.cc/paper/6644-pose-guided-person-image-generation.pdf

CycleGAN

CycleGAN



PixelDTGAN








Super resolution

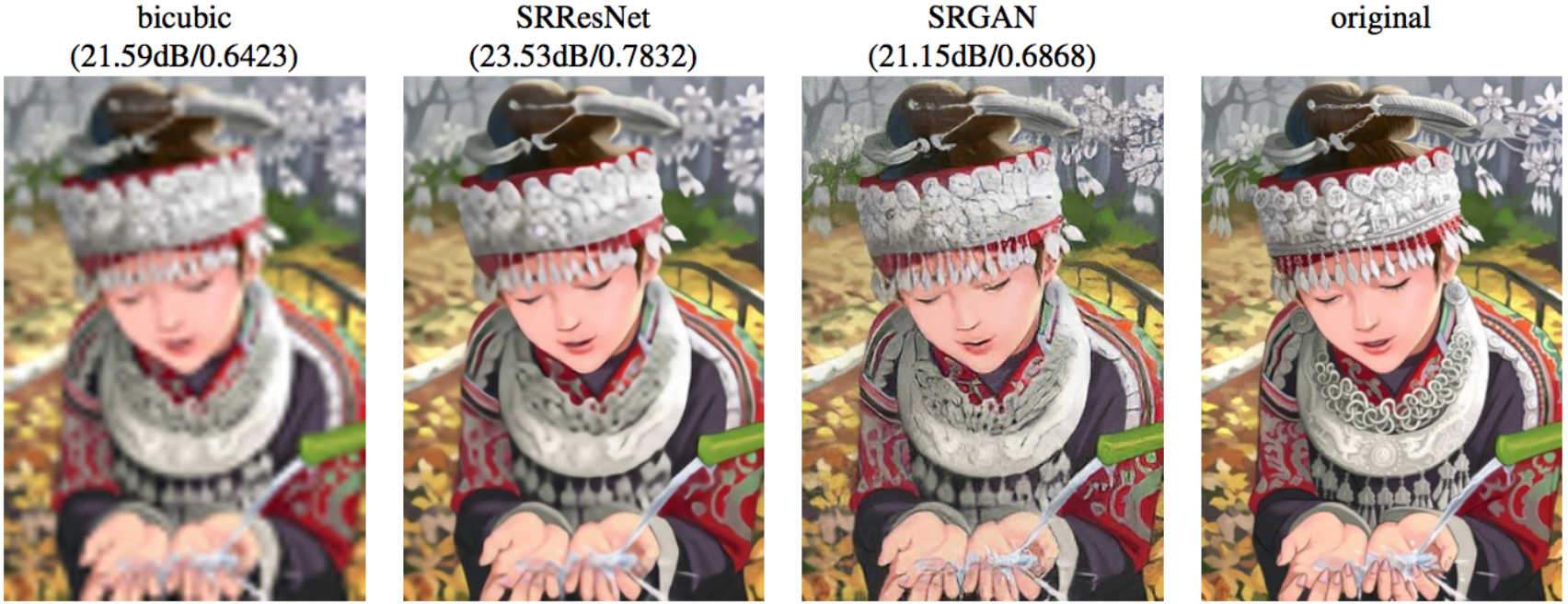


Figure 2: From left to right: bicubic interpolation, deep residual network optimized for MSE, deep residual generative adversarial network optimized for a loss more sensitive to human perception, original HR image. Corresponding PSNR and SSIM are shown in brackets. [4× upscaling]

Progressive GAN

Figure 5: 1024 × 1024 images generated using the CELEBA-HQ dataset. See Appendix F for a larger set of results, and the accompanying video for latent space interpolations.

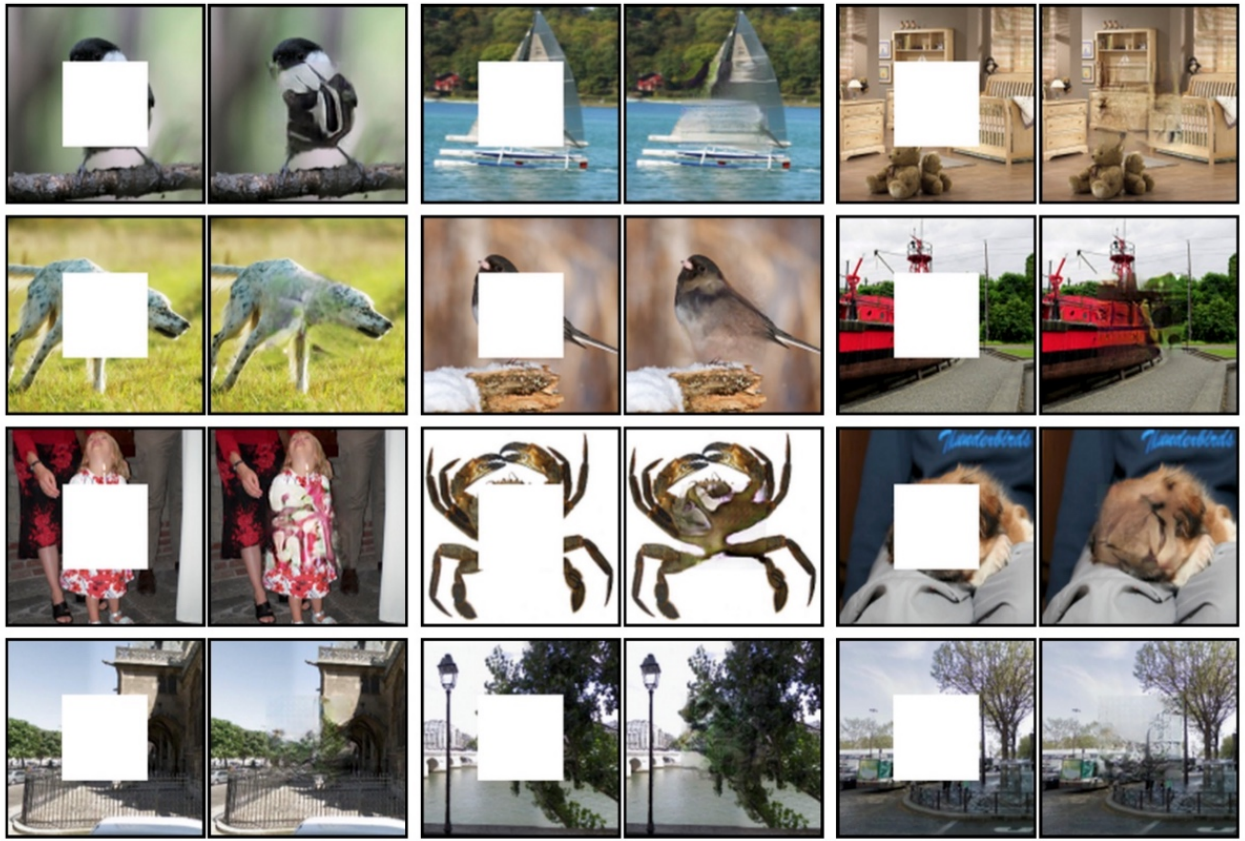
High-resolution image synthesis

Text to image (StackGAN)

Face synthesis

Synthesis results under various illuminations. The first row is the synthesized image, the second r

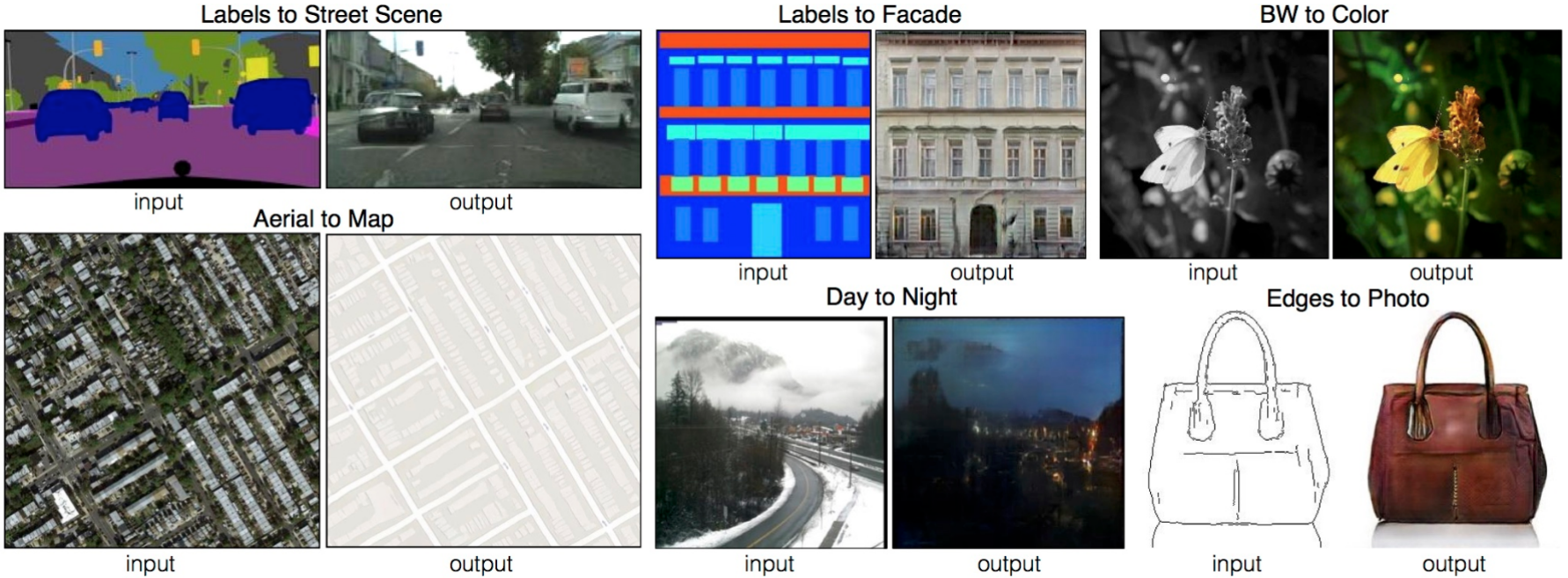
Image inpainting



Matching style - DiscoGAN

(b) Handbag images (input) & **Generated** shoe images (output)

Pix2Pix

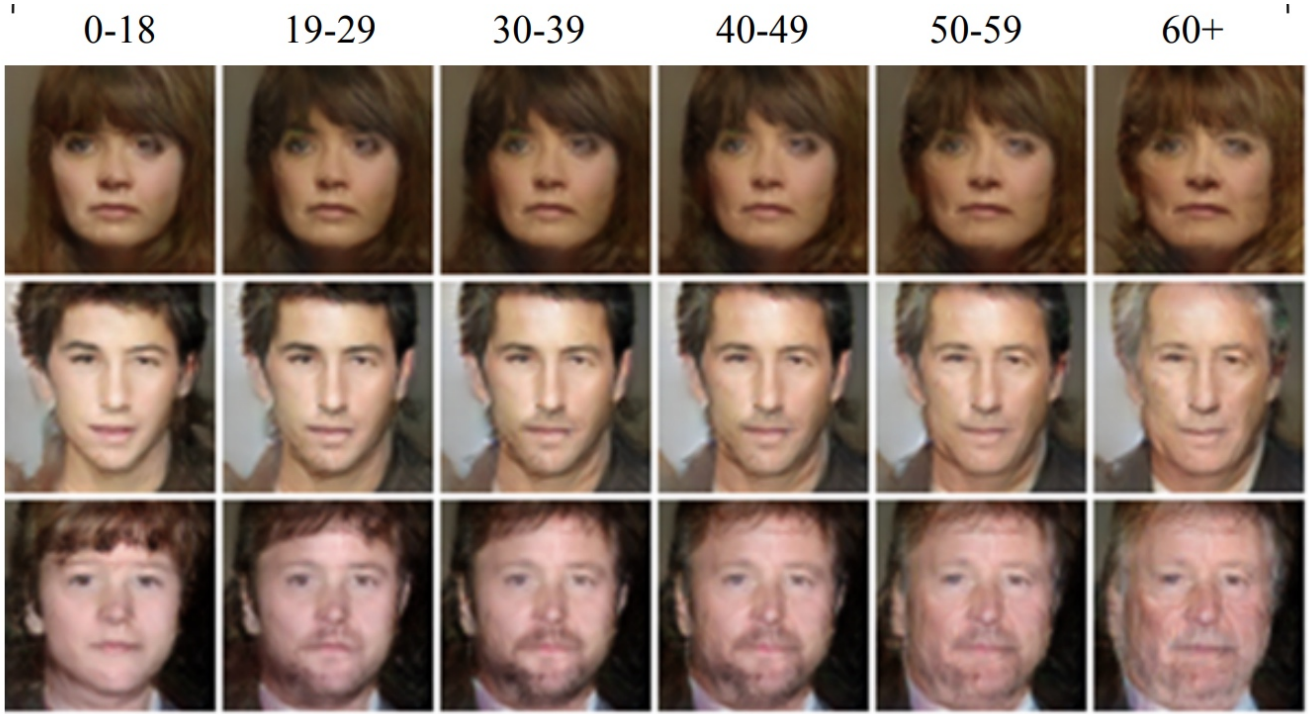

Labels to Street Scene
input
output
Labels to Facade
input
output
BW to Color
input
output
Aerial to Map
input
output
Day to Night
input
output
Edges to Photo
input
output

Emoji from pictures - DTN

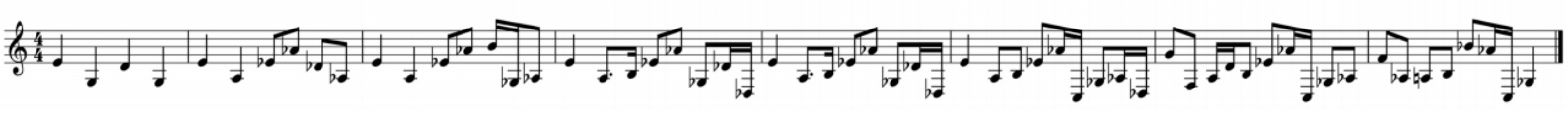
Figure 4: Shown, side by side are sample images from the CelebA dataset, the emoji images created manually using a web interface (for validation only), and the result of the unsupervised DTN. See Tab. 4 for retrieval performance.

Image editing (IcGAN)

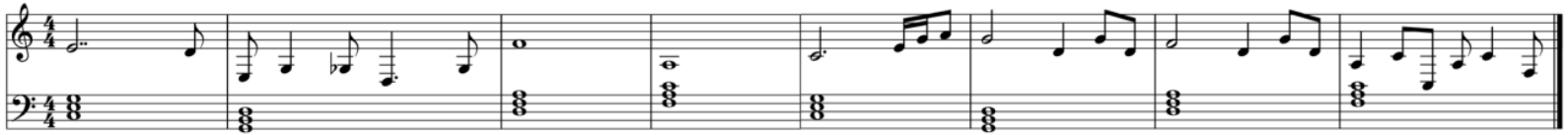
Face aging (Age-cGAN)



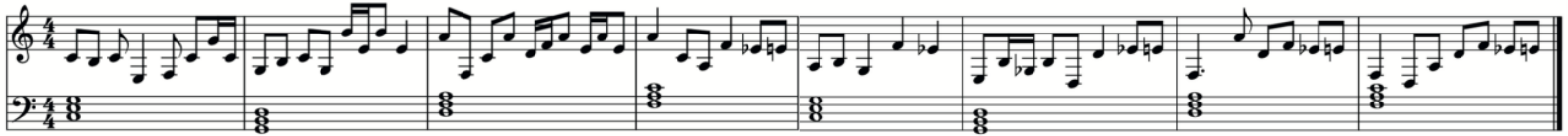
Music generation



(a) MidiNet model 1



(b) MidiNet model 2

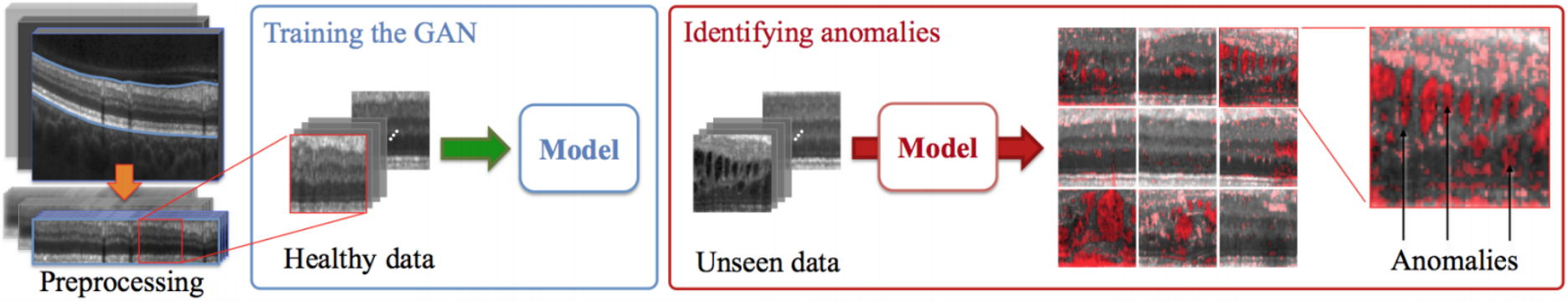


(c) MidiNet model 3

Figure 3. Example result of the melodies (of 8 bars) generated by different implementations of MidiNet.

https://salu133445.github.io/musegan/results

Medical (Anomaly Detection)

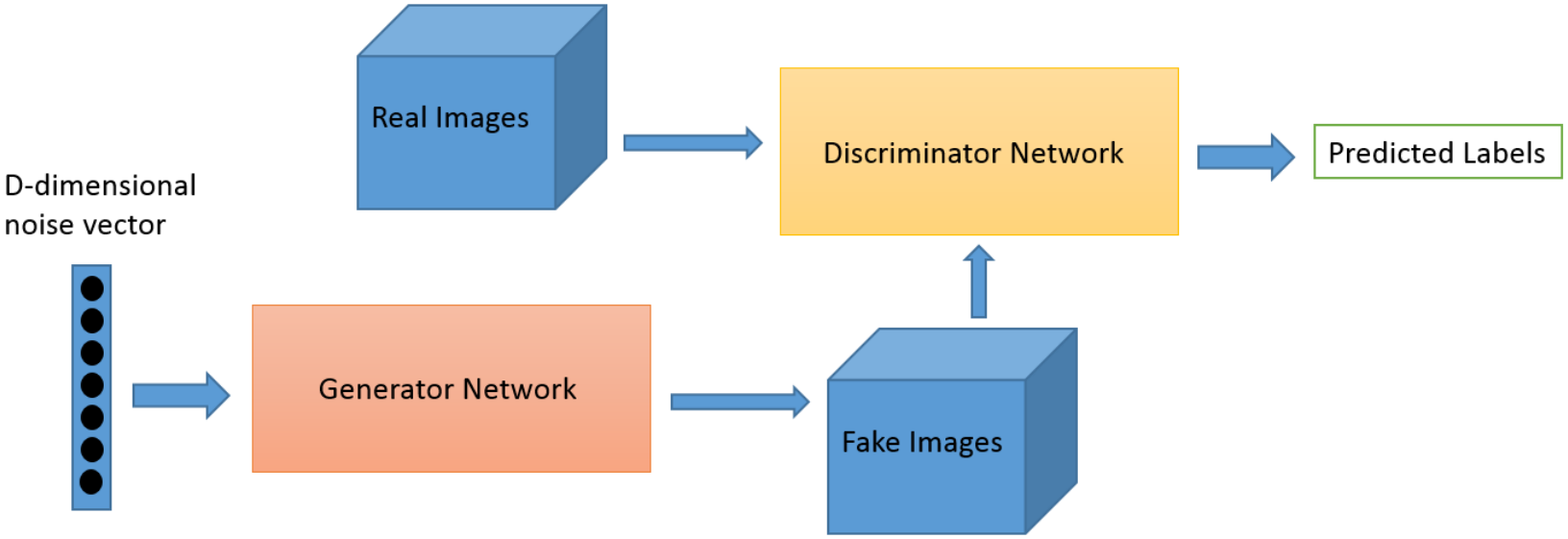


Generative Adversarial Models

Generative	vs.	Discriminative
• generate samples		• classify input data
class label y => sample x		sample x => class label y

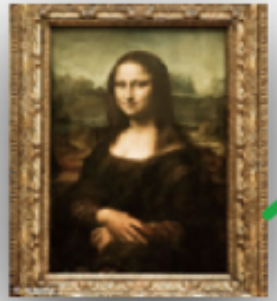
Examples

Generative Adversarial Models



Examples, akin to counterfeiter vs. cop

D: Detective



R: Real Data

G: Generator (Forger)

I: Input for Generator

Interactive playground

- https://affinelayer.com/pixsrv/

```
class GAN():
    def __init__(self):
        self.img_rows = 28
        self.img_cols = 28
        self.channels = 1
        self.img_shape = (self.img_rows, self.img_cols, self.channels)
        self.latent_dim = 100

        optimizer = Adam(0.0002, 0.5)

        # Build and compile the discriminator
        self.discriminator = self.build_discriminator()
        self.discriminator.compile(loss='binary_crossentropy',
            optimizer=optimizer,
            metrics=['accuracy'])

        # Build the generator
        self.generator = self.build_generator()

        # The generator takes noise as input and generates imgs
        z = Input(shape=(self.latent_dim,))
        img = self.generator(z)

        # For the combined model we will only train the generator
        self.discriminator.trainable = False

        # The discriminator takes generated images as input and
determines validity
        validity = self.discriminator(img)

        # The combined model  (stacked generator and discriminator)
        # Trains the generator to fool the discriminator
        self.combined = Model(z, validity)
        self.combined.compile(loss='binary_crossentropy',
optimizer=optimizer)
```

```
def build_generator(self):
        model = Sequential()
        model.add(Dense(256, input_dim=self.latent_dim))
        model.add(LeakyReLU(alpha=0.2))
        model.add(BatchNormalization(momentum=0.8))
        model.add(Dense(512))
        model.add(LeakyReLU(alpha=0.2))
        model.add(BatchNormalization(momentum=0.8))
        model.add(Dense(1024))
        model.add(LeakyReLU(alpha=0.2))
        model.add(BatchNormalization(momentum=0.8))
        model.add(Dense(np.prod(self.img_shape),
activation='tanh'))
        model.add(Reshape(self.img_shape))

        model.summary()
        noise = Input(shape=(self.latent_dim,))
        img = model(noise)

        return Model(noise, img)
```

```
def build_discriminator(self):

        model = Sequential()
        model.add(Flatten(input_shape=self.img_shape))
        model.add(Dense(512))
        model.add(LeakyReLU(alpha=0.2))
        model.add(Dense(256))
        model.add(LeakyReLU(alpha=0.2))
        model.add(Dense(1, activation='sigmoid'))
        model.summary()

        img = Input(shape=self.img_shape)
        validity = model(img)

        return Model(img, validity)
```

```
def train(self, epochs, batch_size=128,
sample_interval=50):
        # Load the dataset
        (X_train, _), (_, _) = mnist.load_data()

        # Rescale -1 to 1
        X_train = X_train / 127.5 - 1.
        X_train = np.expand_dims(X_train, axis=3)

        # Adversarial ground truths
        valid = np.ones((batch_size, 1))
        fake = np.zeros((batch_size, 1))
```

```
if __name__ == '__main__':
    gan = GAN()
    gan.train(epochs=30000, batch_size=32,
sample_interval=200)
```

```
for epoch in range(epochs):

    # ---------------------
    #  Train Discriminator
    # ---------------------

    # Select a random batch of images
    idx = np.random.randint(0, X_train.shape[0], batch_size)
    imgs = X_train[idx]

    noise = np.random.normal(0, 1, (batch_size, self.latent_dim))

    # Generate a batch of new images
    gen_imgs = self.generator.predict(noise)

    # Train the discriminator
    d_loss_real = self.discriminator.train_on_batch(imgs, valid)
    d_loss_fake = self.discriminator.train_on_batch(gen_imgs, fake)
    d_loss = 0.5 * np.add(d_loss_real, d_loss_fake)

    # ---------------------
    #  Train Generator
    # ---------------------

    noise = np.random.normal(0, 1, (batch_size, self.latent_dim))

    # Train the generator (to have the discriminator label samples as valid)
    g_loss = self.combined.train_on_batch(noise, valid)

    # Plot the progress
    print ("%d [D loss: %f, acc.: %.2f%%] [G loss: %f]" % (epoch, d_loss[0],
    100*d_loss[1], g_loss))

    # If at save interval => save generated image samples
    if epoch % sample_interval == 0:
        self.sample_images(epoch)
```

- All codes are on this Colab link:
  - simpleGAN: https://colab.research.google.com/drive/1aZeqH2ssCaEF9OMG8eP8jh93BT0EzWHo
  - discoGAN: https://colab.research.google.com/drive/1hd_eShZaNt5FTVdOrVXFDLCm2zI_9svx
  - cycleGAN: https://colab.research.google.com/drive/1qw2Qr-rOoclY7c9UEdP_4wrLlhsJnBpy

More GAN codes on Keras & Pytorch

- https://github.com/eriklindernoren/Keras-GAN
- https://github.com/eriklindernoren/PyTorch-GAN

Useful resources

- http://speech.ee.ntu.edu.tw/~tlkagk/talk.html
- http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture12.pdf

- https://medium.com/@jonathan_hui/gan-some-cool-applications-of-gans-4c9ecca35900