Resolution Reconstruction of Climate Data with Pixel Recursive Model for Identifying Extreme Climate Events

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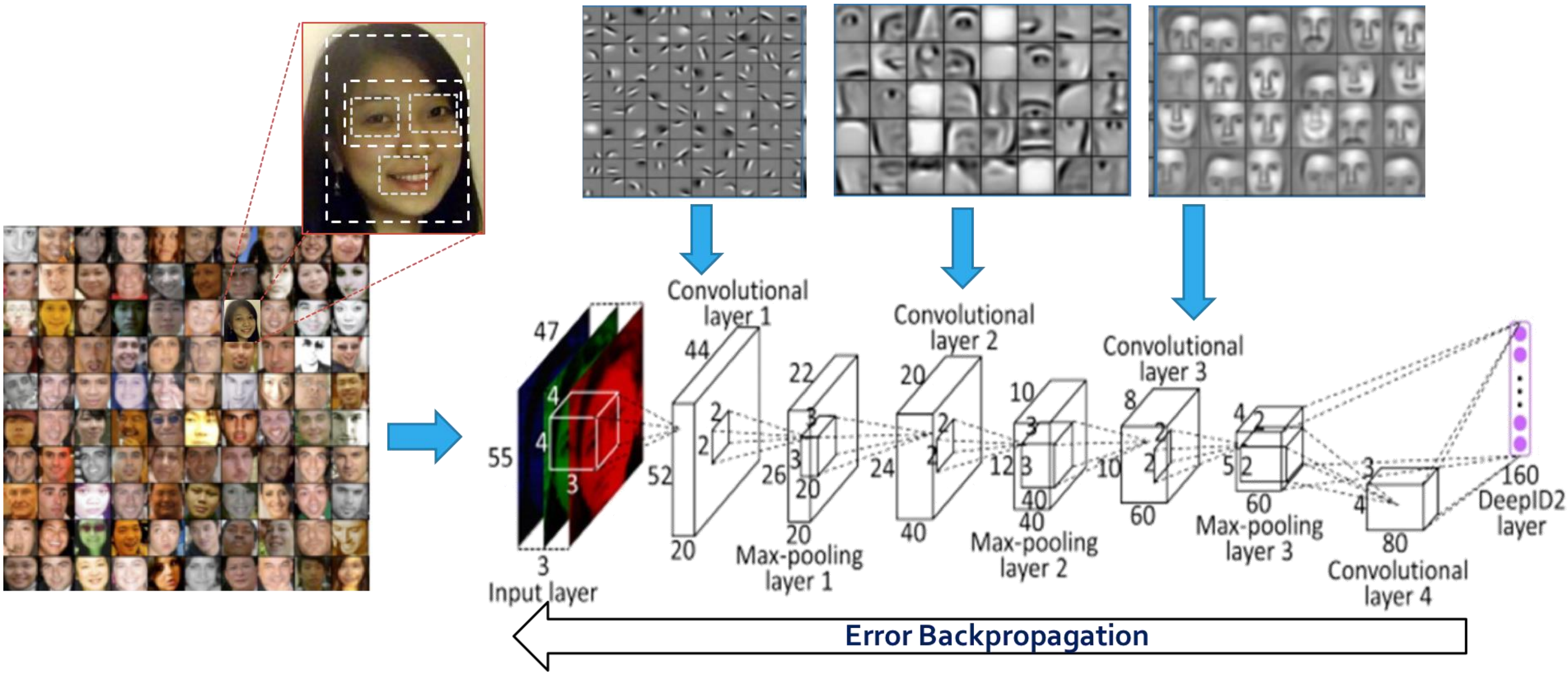
Outline

- **Motivation**
- **Detection and Localization of Extreme Climate Events**
  - **Background:** Convolutional Neural Networks (CNNs)
  - **Method**
  - **Data**
  - **Results**
- **Resolution Reconstruction of Climate Data**
  - **Backgrounds:** Auto-regressive Generative Models
  - **Method:** Pixel-recursive super resolution Model
  - **Data**
  - **Results**
- **Summary**

Deep Neural Network

- Deep convolutional neural networks (CNNs) learn hierarchical feature representation of data

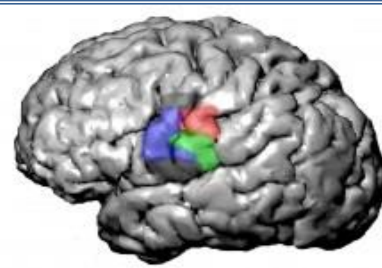


Deep Learning enable science

Ames Research Center

Classify satellite images for carbon monitoring

BERKELEY LAB



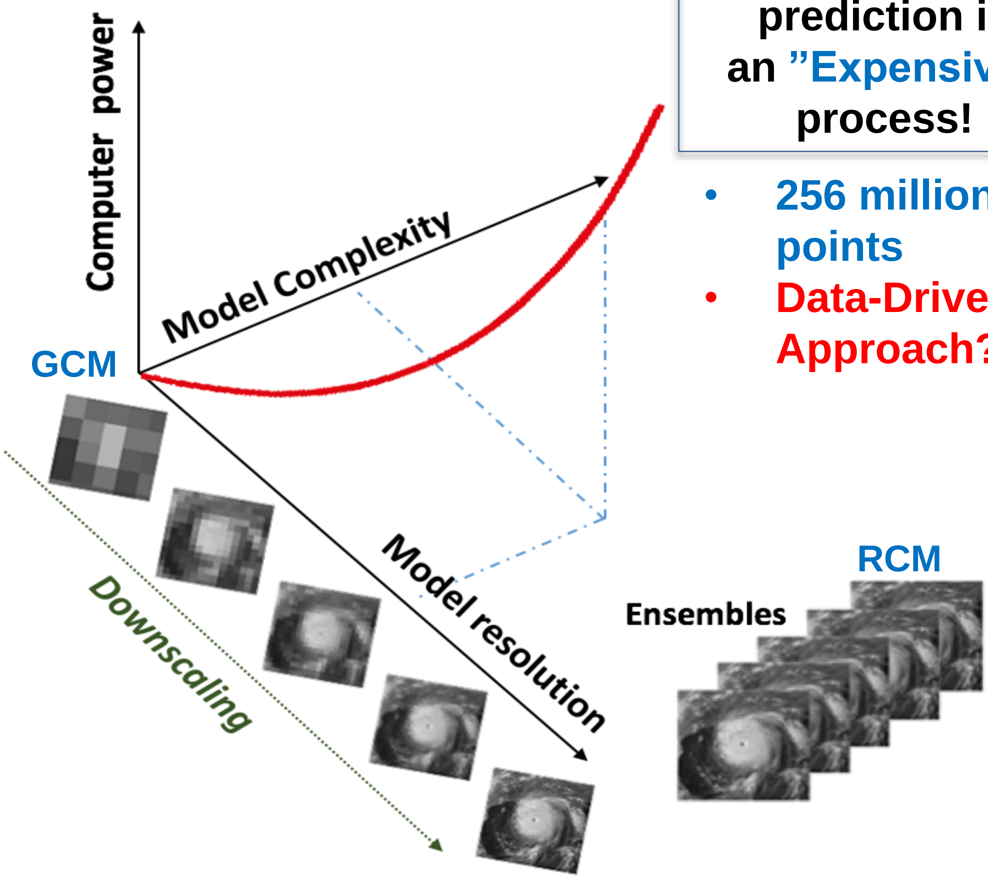
Analyze recording of human brain

OAK RIDGE National Laboratory

Analyze obituaries for Cancer-related discoveries

Deep Learning enable Science!

Motivation



Numerical weather prediction is an "Expensive" process!

- **256 million grid points**
- **Data-Driven Approach?**

- **Only way** to **analyze Peta scaled data** in ESGF
- Let CNNs **learn feature** representation of extreme climate events **in GCM outputs**
- Ultimately **save computing cost** for Numerical Weather Predictions

Method

Comparison with prior approach

TECA from LBNL

(Toolkit for Extreme Climate Analysis)

Pattern Analysis of Climate Data
from **Scientific Definition**

Read un-labeled Data

Threshold:
Vorticity maxima
Pressure minima
Temp warm-core
→ Storm Center

Spatial Constraints

Candidate Location

- **Hand-Crafted Features(filter)**
- Requires high resolution data (~28km)
- Incapability of capturing latent patterns of climate events.

Our Approach

Pattern Analysis of Extreme Climate Data
with **Deep Learning**

Labeled Data

Un-labeled Data

Semi supervised Learning

Read labeled Data

Train CNN

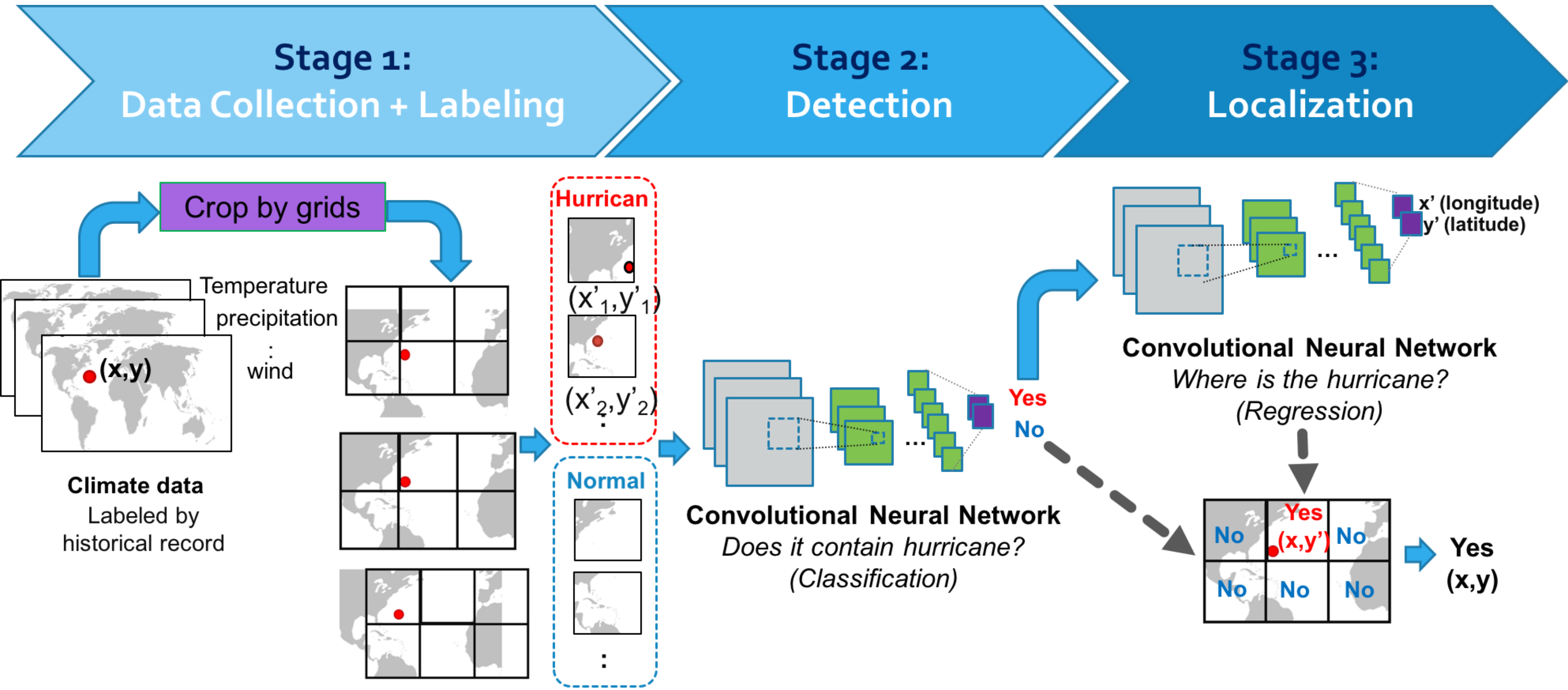
New Input

Detect Climate Event

- **Learned Features (Filter)** from data
  → **No need for prior algorithmic definition**
- Low resolution ~140 km
  →**Detect using GCM**
- Capability to capture latent climate patterns
  →**Scientific exploration**

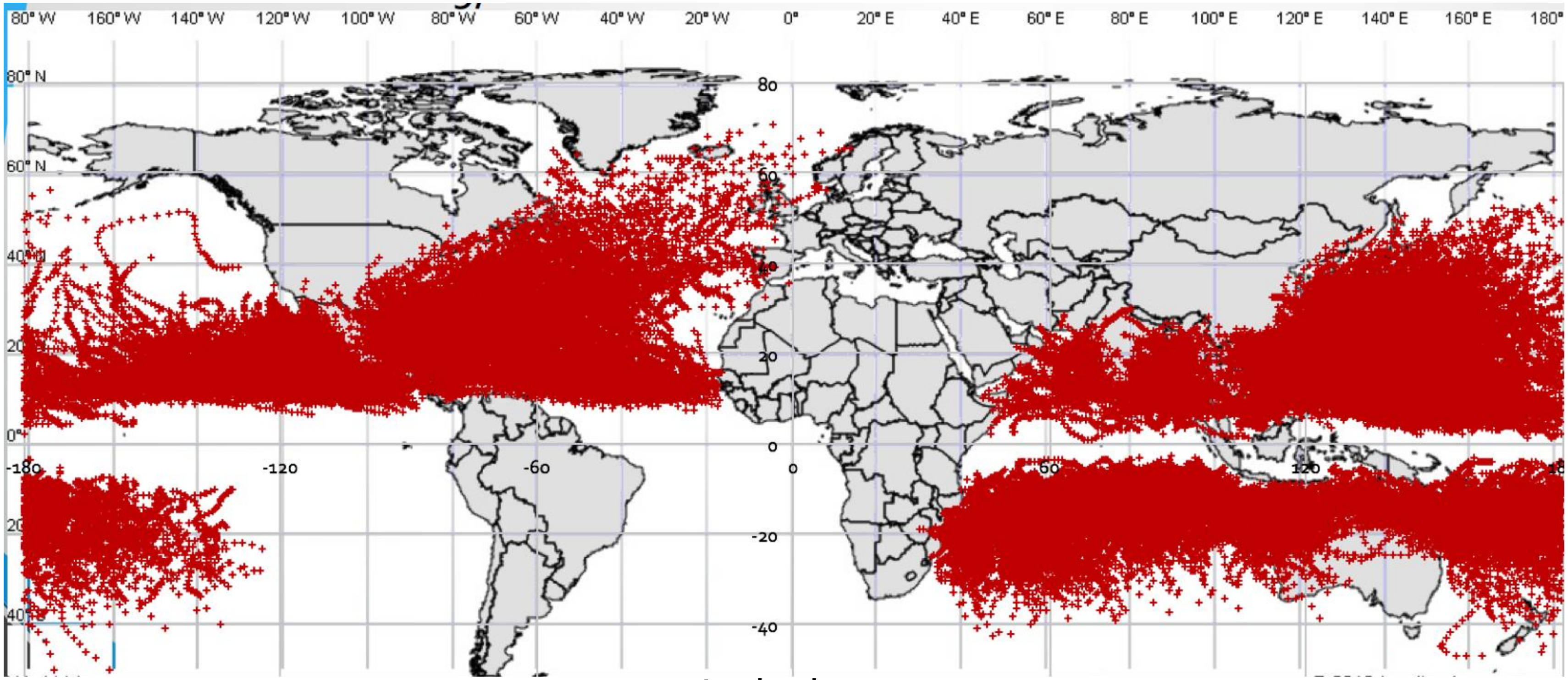
Rübel, Oliver, et al. "Teca: A parallel toolkit for extreme climate analysis." Procedia Computer Science 9 (2012): 866-876.

Method


Stage 1:
Data Collection + Labeling
Stage 2:
Detection
Stage 3:
Localization
Crop by grids
Temperature
precipitation
:
wind
(x,y)
Climate data
Labeled by
historical record
Hurrican
(x'1,y'1)
(x'2,y'2)
:
Normal
:
Convolutional Neural Network
Does it contain hurricane?
(Classification)
Yes
No
x' (longitude)
y' (latitude)
Convolutional Neural Network
Where is the hurricane?
(Regression)
No
Yes
(x,y')
No
No
No
No
Yes
(x,y)

Data

- From JWTC historical hurricane report, 1979 ~ 2016, collected from Japanese 6 hourly reanalysis data
- 5 Channels: cloud fraction, precipitation, surface level pressure, eastward wind, northward wind
- Resolution: 1.25 deg x 1.25 deg (138 km)
- Size of collected grid : 20 longitude by 20 latitude
- Size of dataset: 109,281

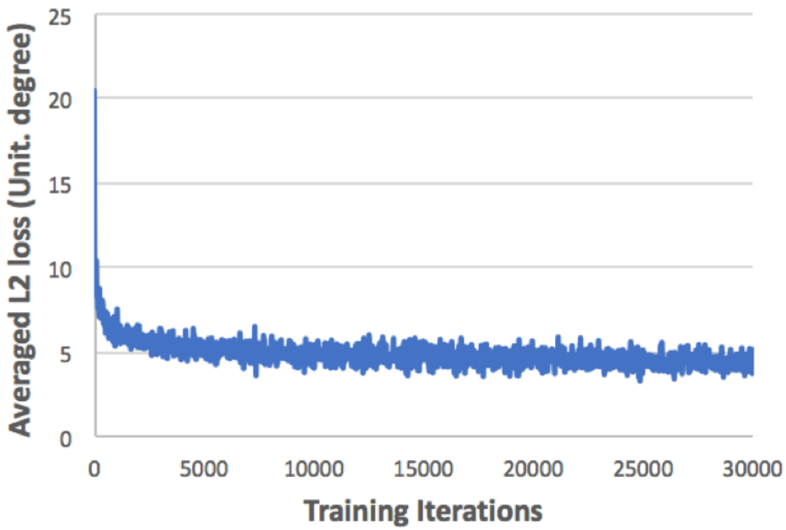


Results

Detection

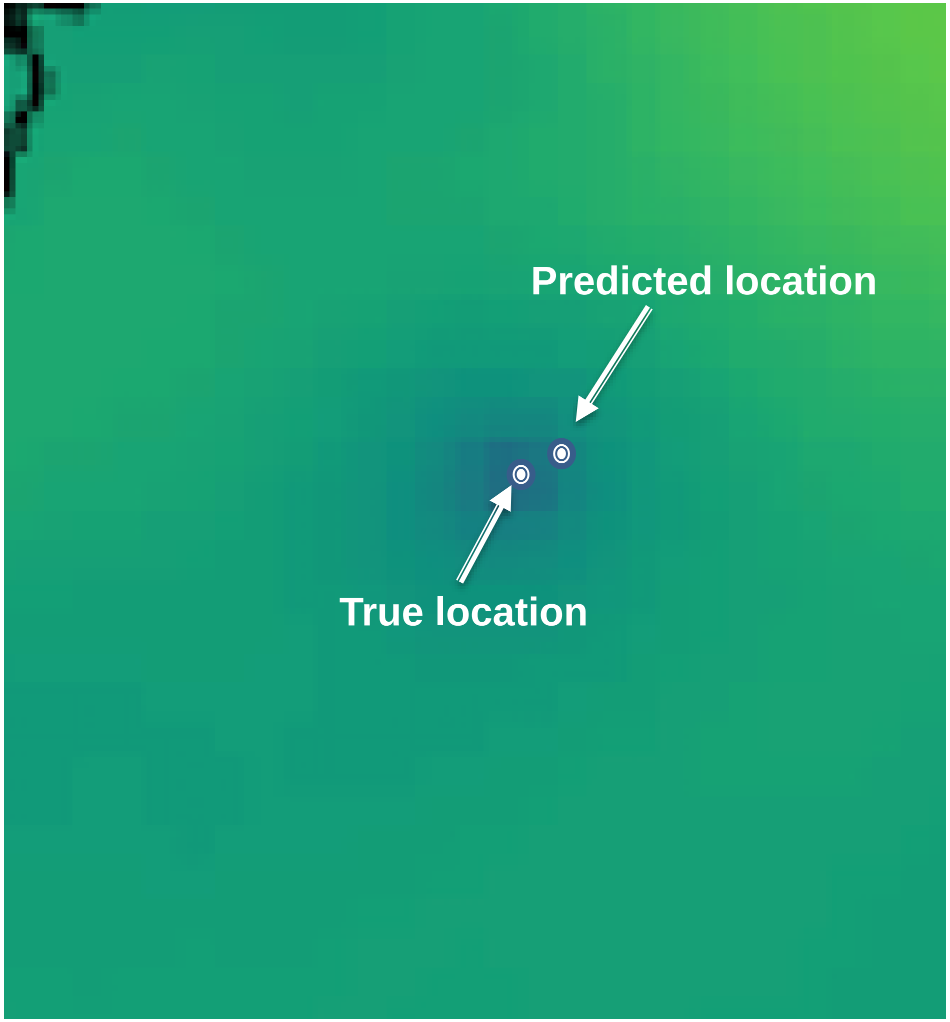
Almost 100 % test accuracy for detection

Localization



Regression error (L2 loss) is
~ 4 degrees (about 450 km)

Poor Localization Accuracy



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Backgrounds:

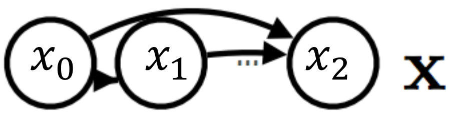
Auto-regressive Generative Models with Deep Learning

- Goal of Generative Model:
  learn probability distribution of data $p(x)$ → Generate (Synthetize) new data

- Auto-regressive Generative Model:
  - choose an ordering of the dimensions in x
  - define the conditionals in the product rule expression of $p(x)$

$$p(x) = \prod_{k=1}^{D} \boxed{p(x_k | X_{<k})}$$

Model with neural nets!



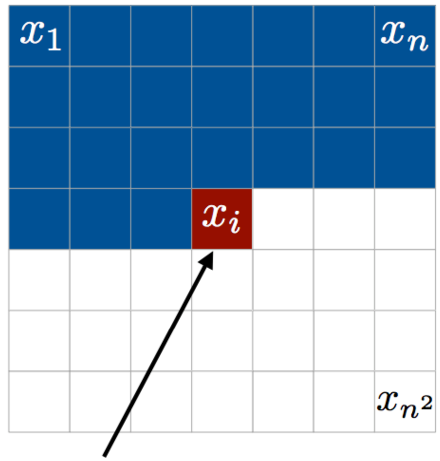
- Properties:
  - Pros: p(x) is tractable, so easy to train with maximum log likelihood, easy to sample
  - Cons: Very very slow, Hard to parallelize with GPU,
    doesn't have a natural latent representation

Backgrounds:

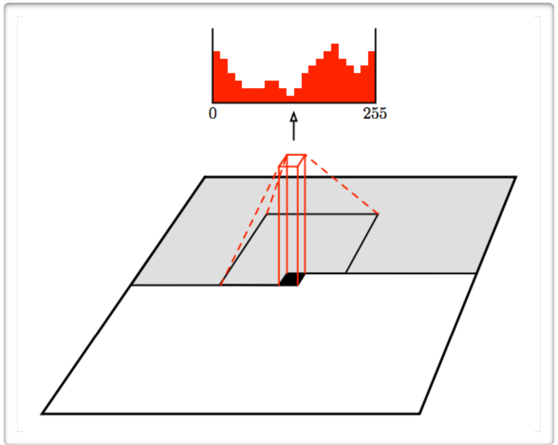
PixelCNN

- Goal of Pixel CNN:
  learn probability distribution of images x, $p(x)$
  by conditioning previous pixels to predict each pixels
  → ***Generate another image y:*** $logP(y|x)$.

- Idea: use masked convolutions to enforce the autoregressive relationship



$$p(x_i \mid \mathbf{x}_{<i})$$

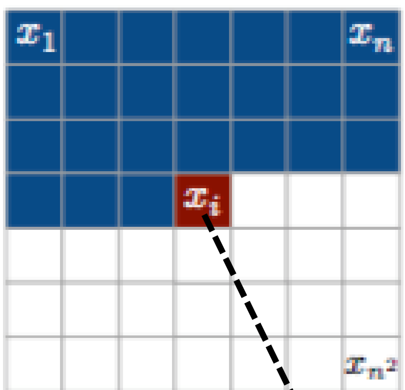


Oord, Aaron van den, Nal Kalchbrenner, and Koray Kavukcuoglu. "Pixel recurrent neural networks." arXiv preprint arXiv:1601.06759 (2016).

Backgrounds:

PixelCNN

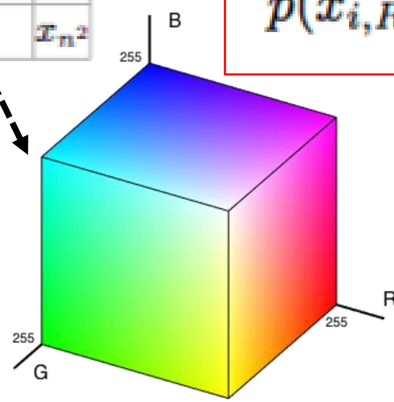
- *Generating am Image x, pixel by pixel, channel by channel*



– $x = x_1, x_2, x_3 \ \dots x_{n\wedge 2}$

$$p(\mathbf{x}) = \prod_{i=1}^{n^2} \boxed{p(x_i | x_1, \dots, x_{i-1})}$$

$$\boxed{p(x_{i,R}|\mathbf{x}_{<i})p(x_{i,G}|\mathbf{x}_{<i}, x_{i,R})p(x_{i,B}|\mathbf{x}_{<i}, x_{i,R}, x_{i,G})}$$

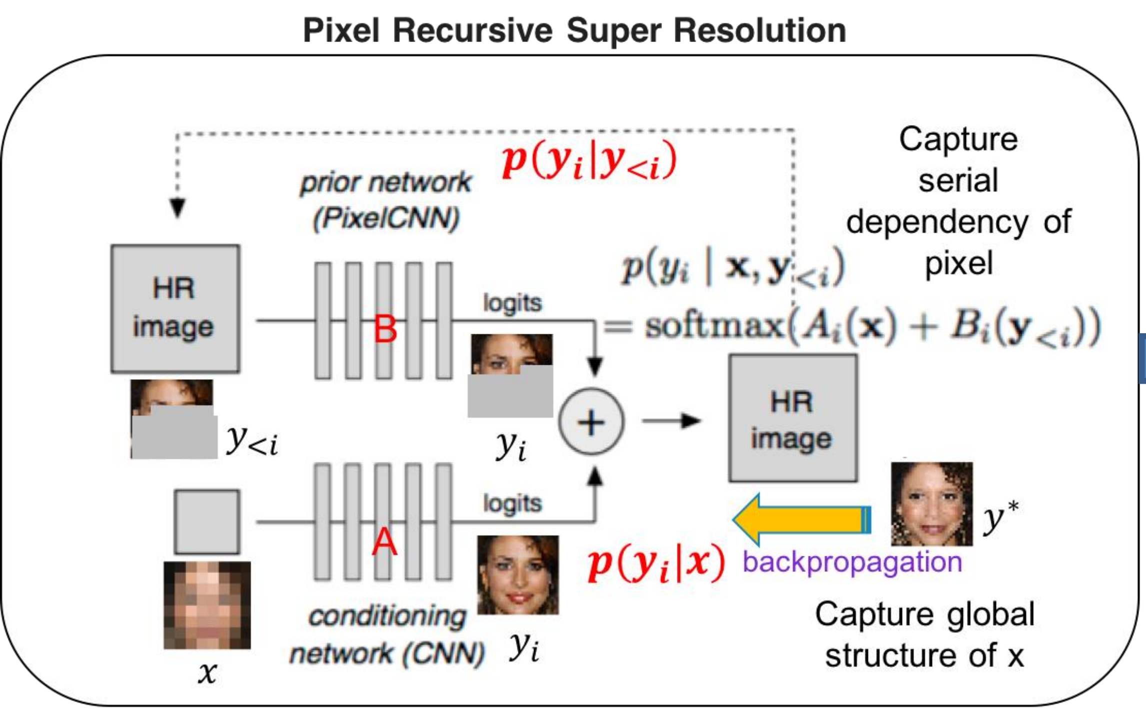


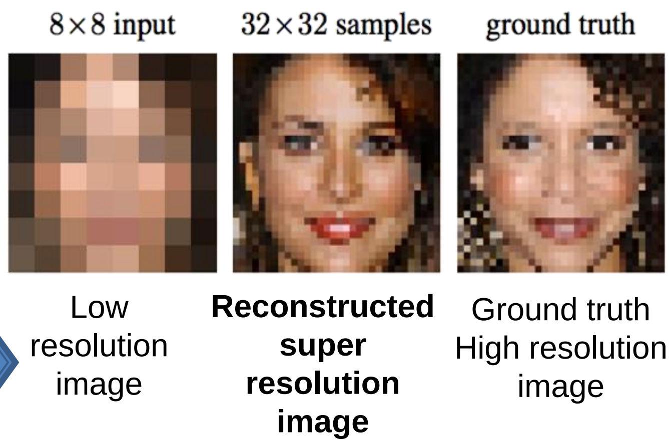
8bit
=256

$x_{i,R} \in R^{256}$
$x_{i,G} \in R^{256}$
$x_{i,B} \in R^{256}$

Method:

Pixel-Recursive Super Resolution Model





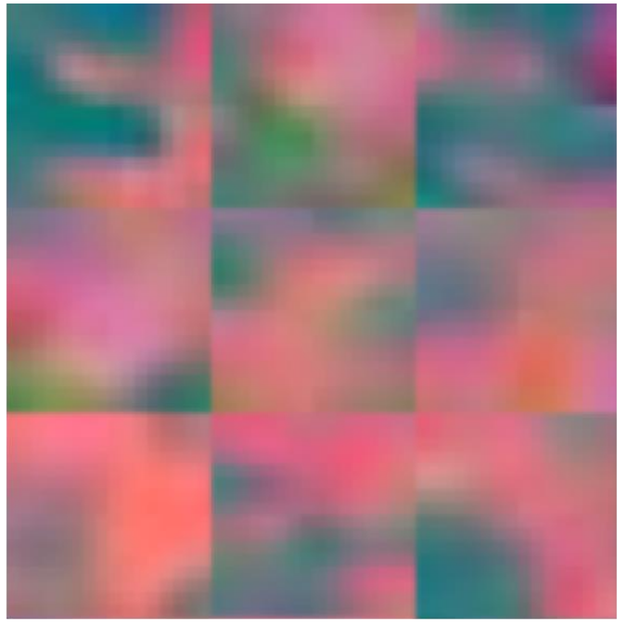
Dahl, Ryan, Mohammad Norouzi, and Jonathon Shlens.
"Pixel recursive super resolution." *arXiv preprint arXiv:1702.00783* (2017)

Data

- Ground truth High resolution image (y)
  - 3 Channels: cloud fraction (Red), eastward wind (Green), northward wind (Blue)
  - Convert variables to 256 integers (Unit8 format)
  - Resolution: 1.25 deg x 1.25 deg (138 km)
- Low resolution image (x)
  - Upscale (x4) high resolution image with bi-cubic interpolation
  - Resolution: 5 deg x 5 deg (552 km)

Results

Low Resolution Image



Super Resolution Image (Generated)

High Resolution Image (Ground Truth)

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Summary

- **Design neural nets to detect extreme climate events**
  - Efficient than hand-crafted filter
  - Save human effort
- Succeed to **detect and localize** tropical cyclone in **GCM scaled low resolution reanalysis data**
  - Potential to reduce expensive downscaling process
  - Save Computing cost
- **Reconstruct High Resolution Climate data** using auto-regressive generative model
  - Potential to improve localization accuracy
  - Alternative with downscaling process
  - Save Computing cost


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