Université de Montréal

Quebec Artificial Intelligence Institute Mila

Solar Irradiance Prediction using Deep Learning

IFT6759 – February 2020 - Project 1 – Team 13

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Agenda

- Project Description
- Solutions Adopted
- Results
- Findings, Obstacles and Recommendations
- Q&A

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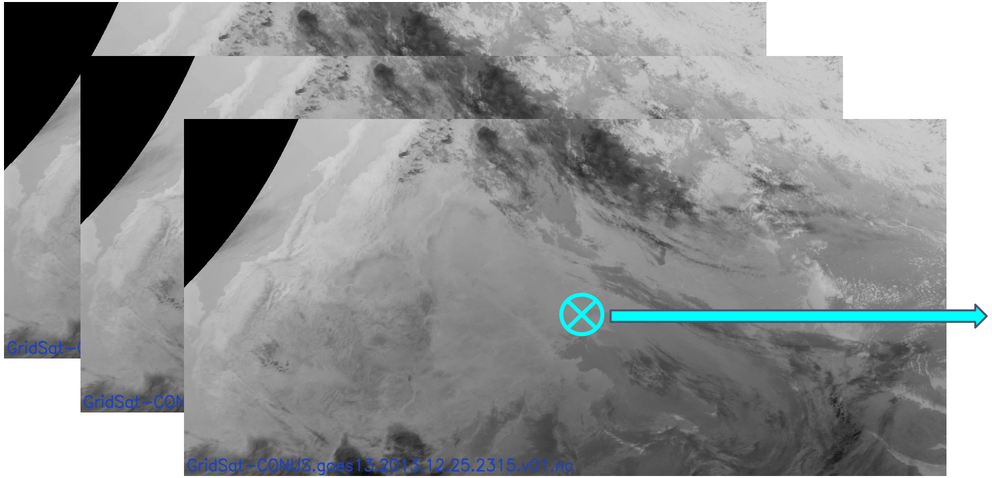
Project Description

Problem Statement

- Given geostationary satellite images up to time T_0, predict Solar Irradiance (GHI, in W/m^2) up to 6 hours ahead
- Not a GHI time series problem



GHI values:

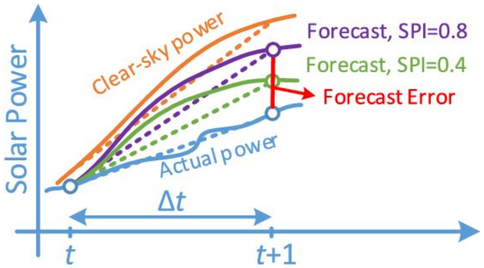
T_0 = 433.2 W/m^2
T_0+ 1h = 443.5 W/m^2
T_0+ 3h = 263.1 W/m^2
T_0+ 6h = -3.2 W/m^2

Project Motivations

- Climate Change
  - Global warming (fossil fuels)

- Large Scale integration of **renewal energy** in the electricity grid
  - Focus on Solar Power

- Why is Solar Power forecasting so important?
  - Intermittent, weather dependent, seasonal
  - Supply-demand electricity market
  - **Cost of Forecast Error**



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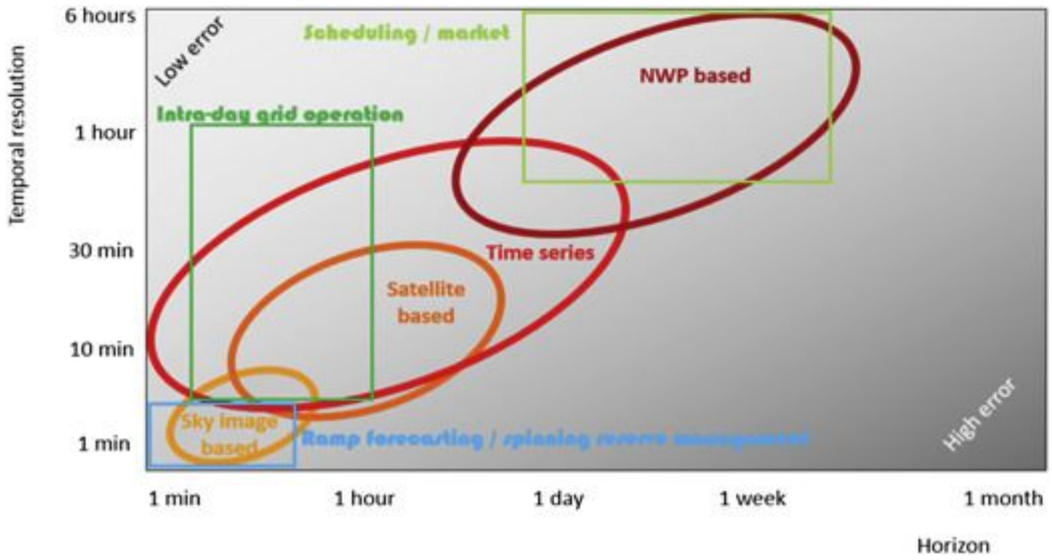
Solar Power forecasting methods



[Machine learning methods for solar radiation forecasting: A review]

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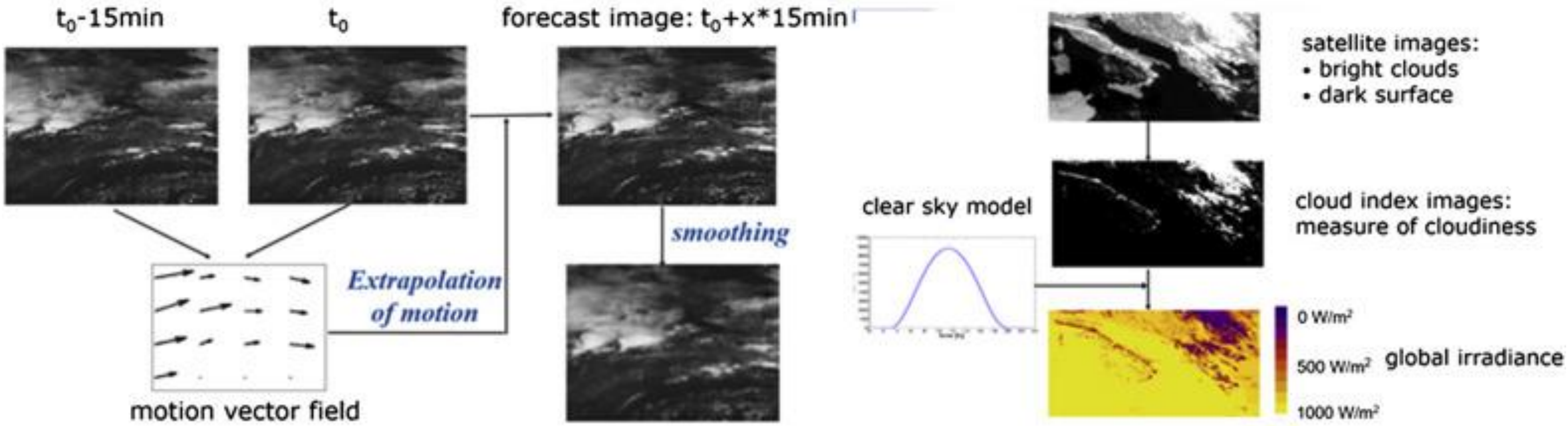
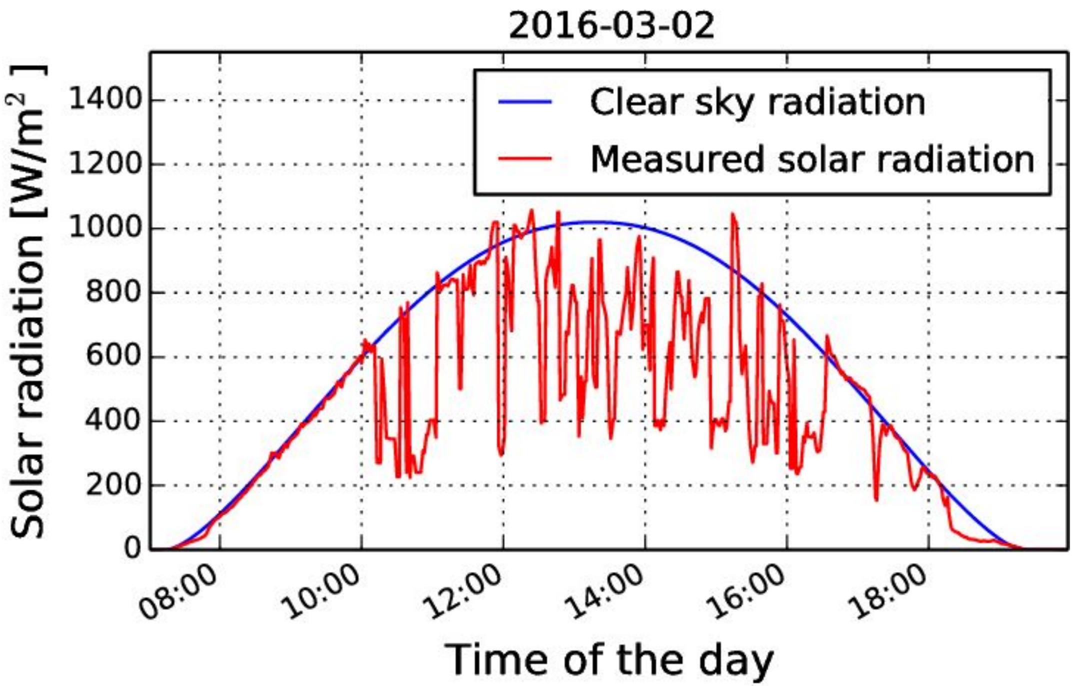
Irradiance forecast using Cloud Motion Vectors



Dr Elke Lorenz, Fraunhofer institute for Solar Energy Systems, Germany

Clear Sky Model



Satellite and GHI Data

GOES-13 (Geostationary Operational Environmental Satellite)

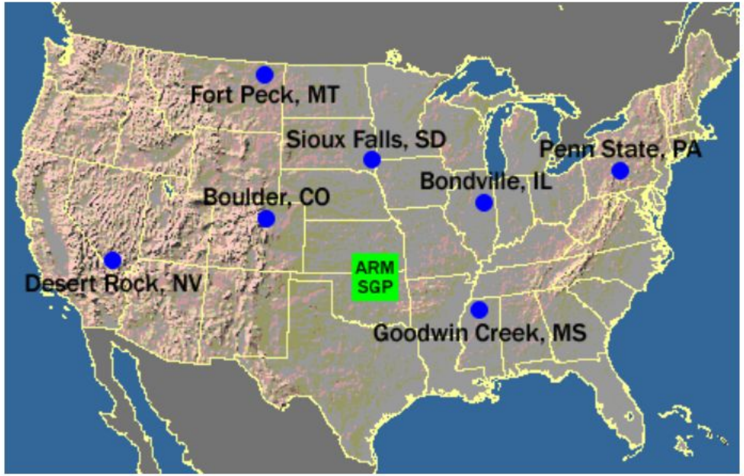
- GOES-13 measures **atmospheric properties**. It is a **geostationary** satellite.
- 5 channels
- From 2010 to 2015, every 15 min
- 3 formats (netcdf, hdf_8bit, hdf_16bit)

Channel	Wavelength	Description
1	550 to 750 nm	Red (visible spectrum)
2	3800 to 4000 nm	Infrared: Smaller wavelengths
3	5800 to 7300 nm	Infrared: Water vapor
4	10,2 to 11,2 μm	Infrared: Bigger wavelengths
5	Not Available	-
6	13,0 to 13,7 μm	Infrared: CO_2

SURFRAD

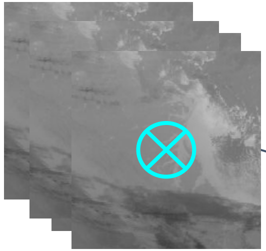
https://www.esrl.noaa.gov/gmd/grad/surfrad/sitepage.html

- GHI measurements at 7 ground stations, from 2010 to 2015 (every 15 min)



Code	Name	Latitude	Longitude	Elevation	Time Zone
BND*	Bondville, Illinois	40.05192° N	88.37309° W	230 m	6 hours from UTC
TBL	Table Mountain, Boulder, Colorado	40.12498° N	105.23680° W	1689 m	7 hours from UTC
DRA	Desert Rock, Nevada	36.62373° N	116.01947° W	1007 m	8 hours from UTC
FPK	Fort Peck, Montana	48.30783° N	105.10170° W	634 m	7 hours from UTC
GWN	Goodwin Creek, Mississippi	34.2547° N	89.8729° W	98 m	6 hours from UTC
PSU	Penn. State Univ., Pennsylvania	40.72012° N	77.93085° W	376 m	5 hours from UTC
SXF	Sioux Falls, South Dakota	43.73403° N	96.62328° W	473 m	6 hours from UTC

Project Goal



Crops centered around a SURFRAD station

Metadata =
- datetime,
- Latitude ?
- Longitude ?
- Elevation ?

Clear-Sky Model

Deep Learning Toolbox

GHI values:

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Solutions Adopted

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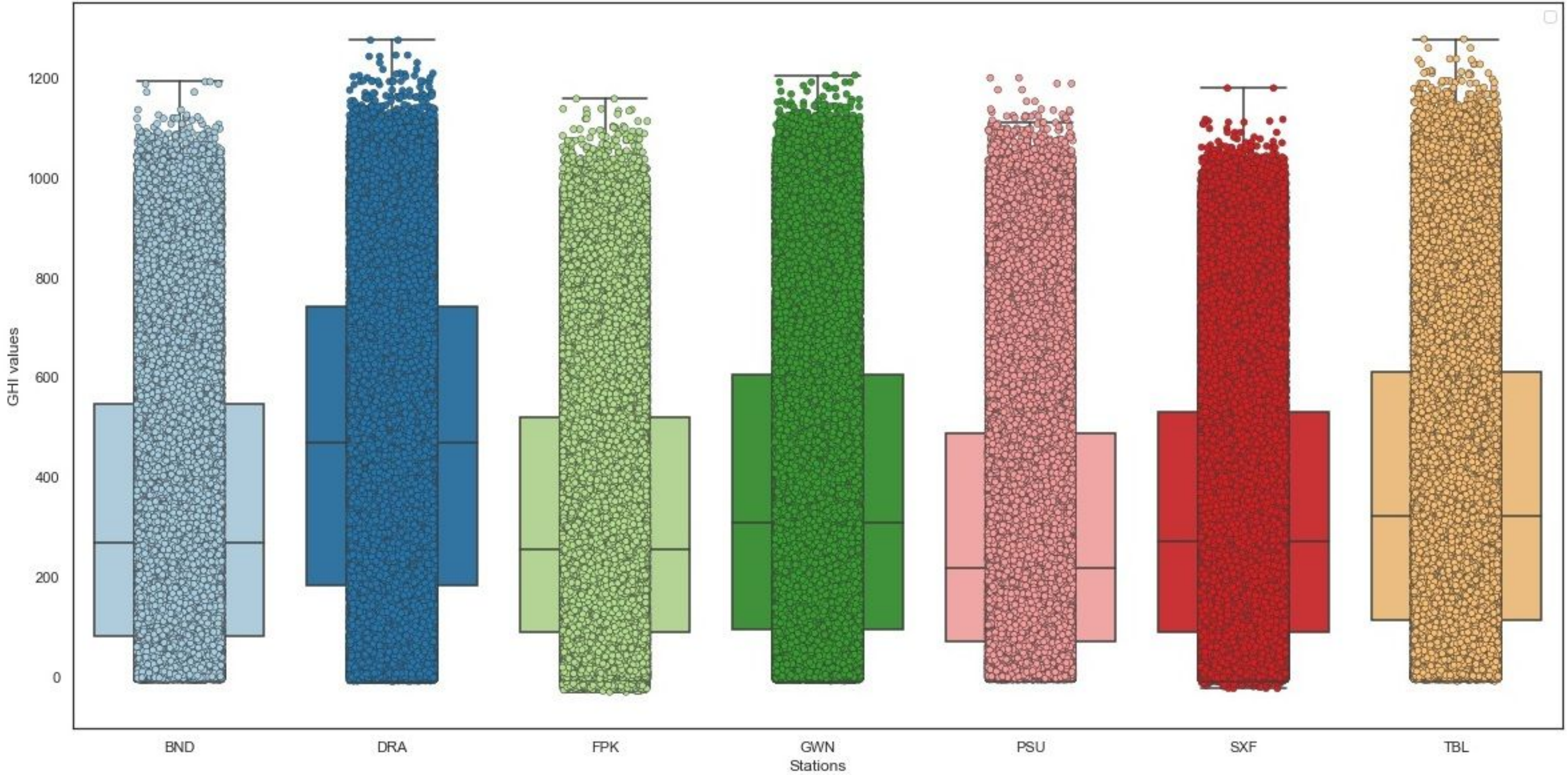
Data Analysis

Data Analysis



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Data Analysis

Clearsky and ground truth GHIs are also missing.
GHI nans (but the nans do not overlap) - Total 6,085

	A	B	C	D
0	12.0	NaN	20.0	14.0
1	4.0	2.0	16.0	3.0
2	5.0	54.0	NaN	NaN
3	NaN	3.0	3.0	NaN
4	1.0	NaN	8.0	6.0

2010	2011	2012	2013	2014	2015
37.21%	12.69%	17.75%	15.81%	10.50%	10.49%

	A	B	C	D
0	12.0	NaN	20.0	14.0
1	4.0	2.0	16.0	3.0
2	5.0	54.0	9.5	4.0
3	3.0	3.0	3.0	5.0
4	1.0	3.0	8.0	6.0

BND	TBL	DRA	FPK	GWN	PSU	SXF
180	514	1258	567	2575	228	763

Data Analysis

We do a train valid test split of 79%-20%-1% on the catalog dataframe, stratified by station, which amounts to 1605 days, 416 days, 26 days in total respectively.

Valid set mostly 2015

We shuffle the rows of the training set as this would enable different seasons and weather conditions in the same batch, hence discouraging the model from learning on just one season or weather condition.

Data Analysis

Dataset	MSE Error	RMSE Error
Train	41300.81	203.23
Valid	44895.35	211.88

Baseline 1: Clearsky on T0 predictions

For 4 GHI predictions at T0, T1, T3, T6
Baseline 2 set by clearsky : 190 RMSE

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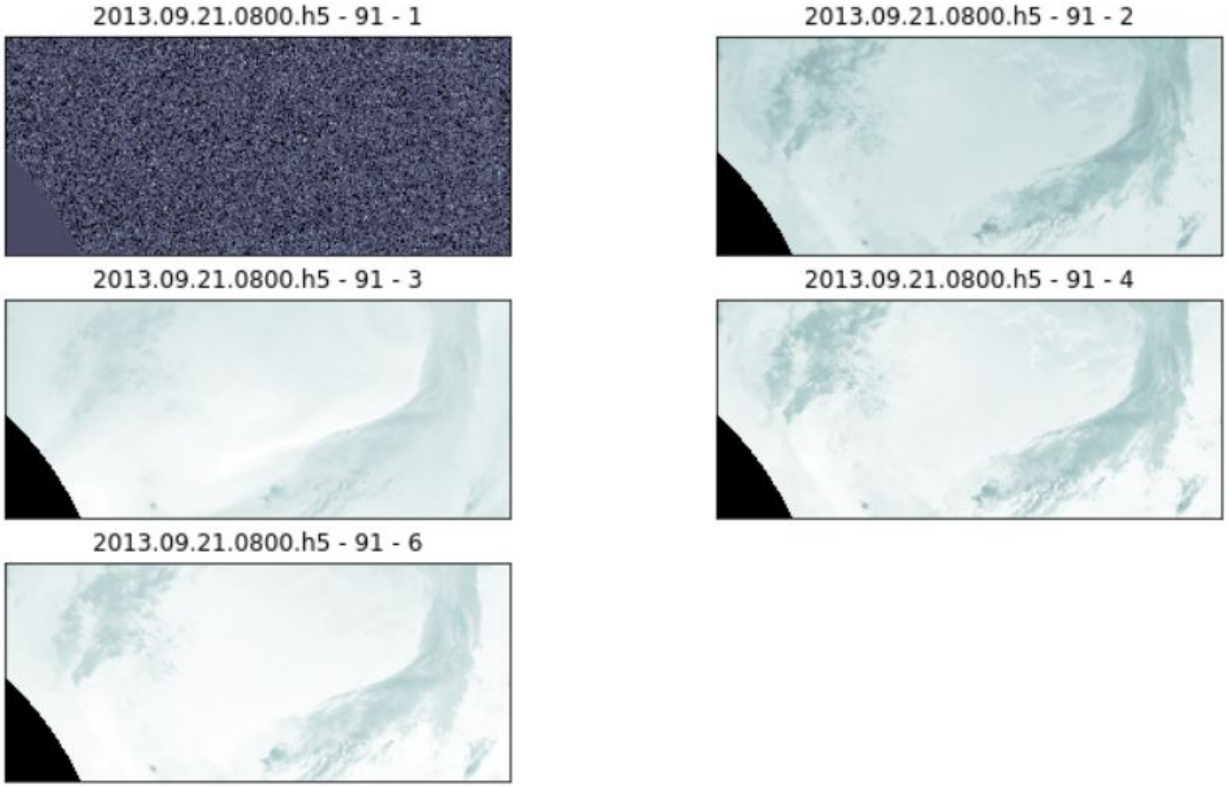
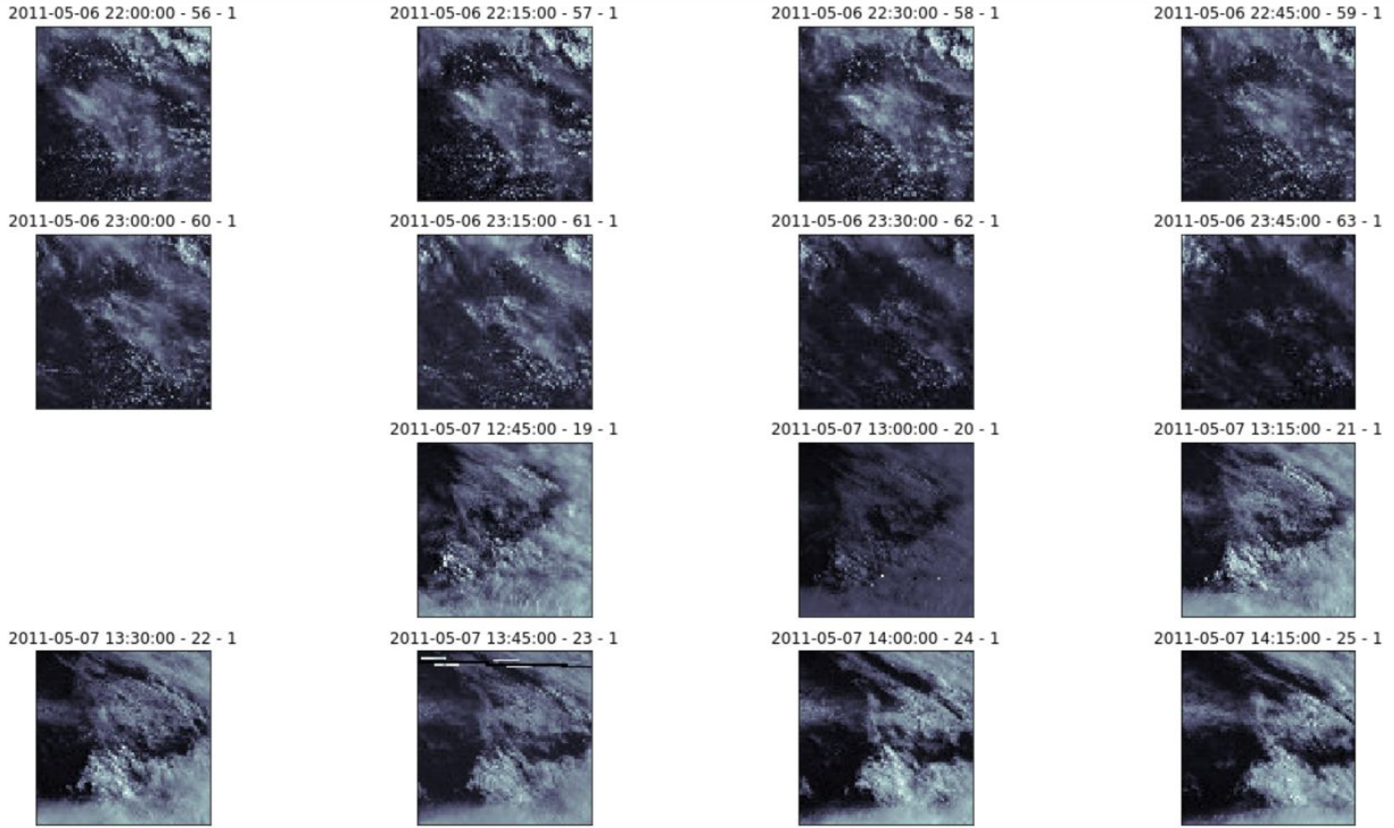
Data Analysis



- Noisy Channel 1
- Histogram based methods

Data Analysis



- 70x70 crop = 280 km2
- 30 minute interval
- 3 time sequences

Dataloader

- Accumulated images of all the offsets in an hdf5 file and stored it to a 4-D numpy array of size [offsets,channels,height,width].
- Handled missing channels by copying channel from the previous time offset.
- Took a crop of 70x70 around all stations:
- Stored station-wise crops into a npz array with stations as the dictionary key
- Iterated through the catalog and yielded individual examples

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Models

Models - 2D CNN

Architecture:

Input = 70x70x5

Convolution(16x3x3)

BatchNorm + ReLU + MaxPool(2)

Convolution(32x3x3)

BatchNorm()

Convolution(64x3x3)

BatchNorm()

Convolution(128x3x3)

BatchNorm()

Convolution(128x5x5)

BatchNorm()

Output = Dense(4)

Models - 3D CNN

Architecture:

Input = 3x70x70x5

Convolution(16,1x3x3)

BatchNorm + ReLU + MaxPool(2x2)

Convolution(32,1x3x3)

BatchNorm()

Convolution(64,1x3x3)

BatchNorm()

Convolution(128,1x3x3)

BatchNorm()

Convolution(256,1x5x5)

BatchNorm()

Output = Dense(4)

Results

Model	Train RMSE	Validation RMSE
2D CNN	100	119
3D CNN	114	168
3D CNN with metadata	116	120

Forecast skill of 2D CNN = 1 - (119/154) = 0.23
(persistence RMSE: 154)

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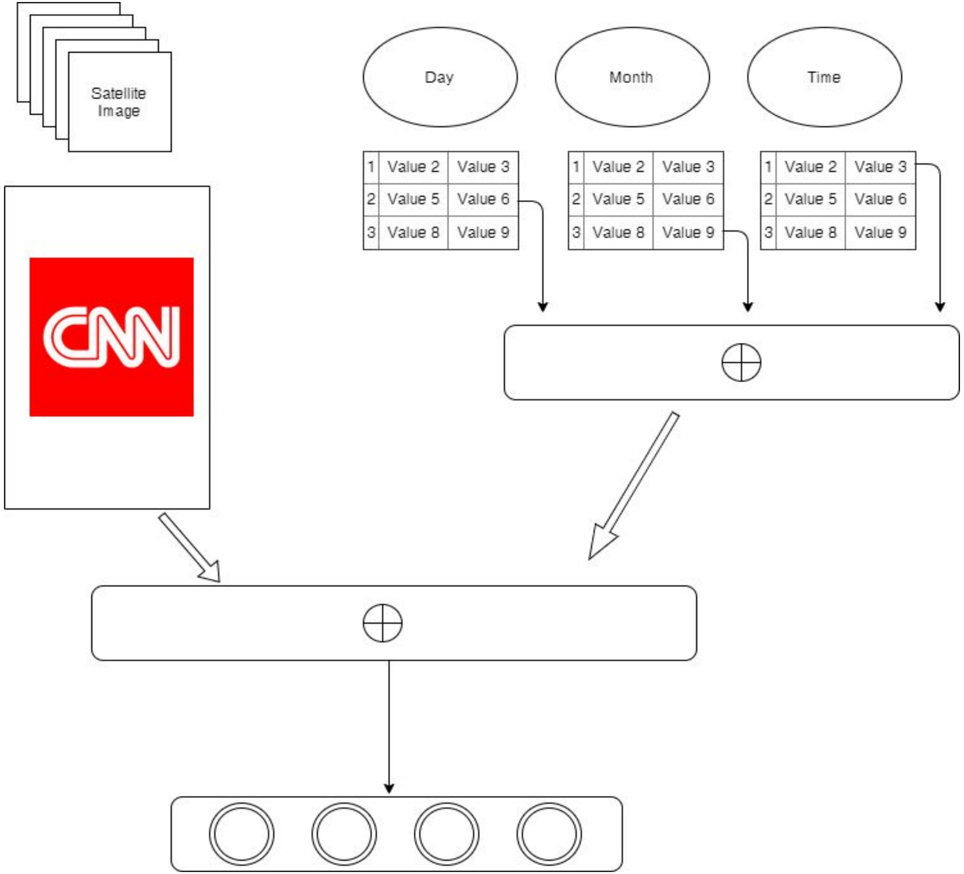
Models: Using Meta-data



- ❌ Latitude
- ❌ Longitude
- ❌ Elevation

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