Seasonal Hurricane Forecasting Using Machine Learning

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Problem Statement

Hurricanes are among the most destructive and costly natural phenomena. Seasonal forecasts of tropical cyclones in the Atlantic can increase public preparedness and yield insights into local and remote climate system influences. A limitation to existing methodologies is use of regression techniques that limit the number of input features and cannot represent nonlinear relationships between the predictors and the output. Neural networks, as universal function approximaters, are largely insensitive the number of input features and can use activations functions that allow for modelling of nonlinear relationships in the data. This project explores the potential for deep learning to provide a new tool for sub-seasonal to seasonal forecasting of tropical cyclone activity in the Atlantic.

Background

Forecasting tropical storms (TS) on a sub-seasonal or seasonal time scale is tractable due to two factors: (1) Tropical SSTs have a significant impact on TS occurrence and intensity; (2) Tropical SSTs are predictable on a seasonal scale. Warm/cold El Niño/Southern Oscillation (ENSO) events are generally associated with less/more TS activity in the Atlantic basin due primarily to their association with increased/decreased wind shear. Two prominent groups engaged in seasonal hurricane forecasting are National Oceanic and Atmospheric Administration's (NOAA) Climate Prediction Center (CPC) and the Colorado State University (CSU) Tropical Meteorological Project, have achieved promising results for two decades.

Key Terms

Named Storms(NS): Tropical cyclones with maximum 1-minute sustained 10 m wind speeds between 39-73 mph

Hurricanes(H): Tropical cyclones with maximum 1-minute sustained 10 m wind speeds of at least 74 mph

Major Hurricanes(MH): Tropical cyclones with maximum 1-minute sustained 10 m wind speeds exceeding 111 mph, categories 3-5 on the Saffir-Simpson hurricane scale

Challenges and Uncertainties

- 1944 is the first year for which complete and reliable tropical cyclone records are considered to exist for the North Atlantic, therefore, empirical methods are limited by the relatively low number of previous years of record.
- Modeling is complicated by well-documented uncertainties associated with the target output hurricane dataset (HURDAT) maintained by the National Hurricane Center (NHC).
- Empirical methods for seasonal hurricane prediction are vulnerable to significant changes in the climate, due for example to interdecadal variability.
- Many combinations of named storms and hurricanes are possible with the same given set of climate observations. For example, one cannot know with certainty whether a given climate signal will be associated with several short-lived storms or fewer longer-lived storms with greater intensity.

Predictors

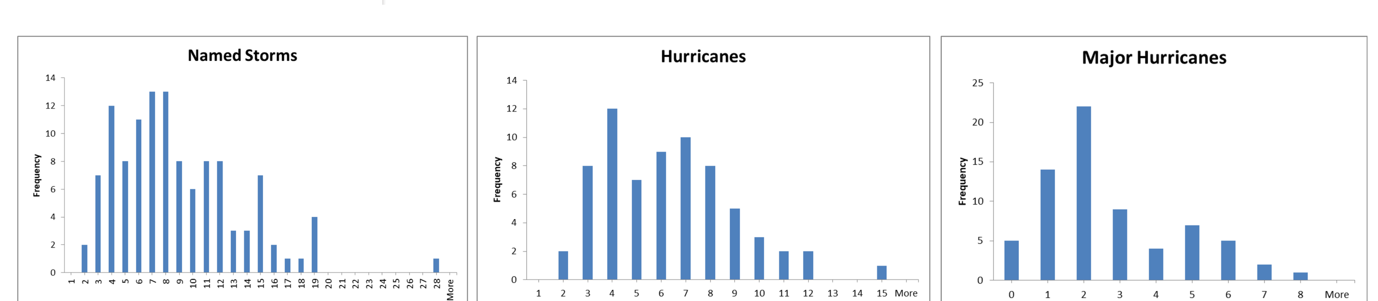
Predictor	Definition	Rationale	References
AMO	Atlantic Multidecadal Oscillation (AMO) - A low frequency SST variability in the Atlantic Ocean.	When AMO is in positive phase, Atlatic tropical storm occurance (especially major hurricanes) increases.	Klotzbach and Gray 2008, Zhang and Delworth 2006,
AMM	Atlantic Meridional Mode (AMM) - Spatial pattern defined by applying Maximum Covariance Analysis (MCA) to sea surface temperature (SST; left field) and the zonal and meridional components of the 10m wind field (right field) over the time period 1950-2005 from the NCEP/NCAR Reanalysis.	AMM is highly correlated to SST, vertical wind shear, low-level vorticity, static stability and SLP. Postive AMM phase is associated with increased Atlantic TC activity. In negative phase, cyclogenesis tends to occur along U.S. east coast near land in less favorable SST and shear environments.	Goldenberg et al. 2001, Kossin and Vimont 2007.
NTAWND	Northern tropical Africa 200-hPa zonal wind in m/s for region between 5°N-15°N, 0°E-40°E.	Anomalous easterly flow at upper levels over northern tropical Africa is more favorable for easterly wave development into TCs and tends to persist through August-October, which reduces shear over the MDR.	Klotzbach et al. 2019
CUWIND	Caribbean 200-hPa zonal wind in m/s for region between 10°N-20°N, 65°W-85°W.	Positive anomalies of 200-hPa zonal wind are associated with enhanced shear and reduced TC activity. Negative anomalies are associated with reduced shear and increased TC activity.	Gray et al. 1994
CSUWND	Caribbean 1000-hPa zonal wind for region between 10°N-17.5°N, 65°W-85°W.	Weaker-than-normal trade winds are associated with elevated Atlantic Warm Pool SSTs, reduced vertical shear in the region, higher pressure in the tropical eastern Pacific (a La Niña signal), and lower pressure in the Caribbean and tropical Atlantic which are all associated with increased Atlantic TC activity.	Gray et al. 1994, Klotzbach et al. 2019
CMLSP	Central Atlantic mean sea level pressure (MSLP) for area between 20°N-40°N, 30°W-50°W.	Low pressure during the month of May in the central Atlantic is associated with reduced trade wind strength promoting reduced upwelling, mixing and enhanced ocean current flow from the south which favors warm anomalies and enhanced Atlantic TC activity. Warm anomalies in Apr-May tend to persist throughout the peak hurricane season.	Klotzbach et al. 2019
CSST	Caribbean SST anomaly for region between 10°N-25°N, 60°W-80°W.	Warm SST anomalies are associated with increased TC activity.	Gray et al. 1994
DMI	Dipole Mode Index (DMI) - Gradient of the Indian Ocean Dipole (IOD) which is the SST gradient between the western equatorial Indian Ocean (50°E-70°E and 10°S-10°N) and the south eastern equatorial Indian Ocean (90°E-110°E and 10°S-0°N).	Significant positive IOD events occur during all phases of ENSO and are typically associated with reduced Atlantic hurricane activity by impacting the west African monsoon circulation and ENSO-related convecton patterns.	Bell et al. 2011
EASST	Eastern Atlantic SST defined for this project as the SST anomalies region between 17.5°-57.5°N, 17.5°W-37.5°W.	Positive SST anomalies in the eastern Atlantic during the April-May period are associated with a weaker-than-normal subtropical high, reduced trade wind strength which are correlated with weaker trade winds, weak upper tropospheric winds, lower SLP, above-normal SST and higher Atlantic TC activity the following August-October.	Klotzbach et al. 2019
NINO3	SST anomaly from the HadISST data set based on climatological average from 1981-2010. Region is 5°N-5°S, 150°W-90°W.	ENSO is the dominant contributor to variance in 200-hPa zonal winds across the MDR. Moderate to strong warm ENSO is associated with reduced TC activity due to stronger than normal westerly winds.	Bell and Chelliah 2006, Goldenbert et al. 2001, Gray et al. 1984
NINO34H	SST anomaly from the HadISST data set based on climatological average from 1981-2010. Region is 5°N-5°S, 170°W-120°W.		
MDRSST	Atlantic hurricane main development region (MDR) SST anomaly from Kaplan SST V2 in the region between 12.5°-22.5°N, 30°W-87.5°W.	Atlantic tropical storm activity is highly correlated to SST conditions in the MDR.	Goldenberg et al. 2001, Zhang and Delworth 2006.
NASST	North Atlantic SST anomaly for region 5°N-17°N, 10°W-60°W.	Warm SST anomalies are associated with increased TC activity.	
NESSTA	Northeast Subtropical Atlantic SST anomaly from the Kaplan SST V2 data set based on climatological average from 1981-2010. Region is 22.5°N-42.5°S, 15°W-35°W.	Anomalously warm SSTs in the subtropical North Atlantic are associated with reduced trade wind strength are associated with less surface evaporative cooling and less mixing and upwelling. This results in warmer tropical Atlantic SSTs during the August-October period.	Klotzbach et al. 2019
NAO	Hurrel North Atlantic Oscillation (NAO) index. The principal component (PC)-based indices of the North Atlantic Oscillation (NAO) are the time series of the leading Empirical Orthogonal Function (EOF) of SLP anomalies over the Atlantic, 20°-80°N, 90°W-40°E.	By controlling the positon of the Azores High, NAO influences the general storm paths for major N Atlantic Hurricanes. Positon of H farther south tends to focus storms into the Gulf of Mexico. The position of the H is also linked to strength of the trade winds.	Elsner and Jagger 2006
QBO	Quasi-biennial oscillation (QBO). The monthly and zonal mean equatorial zonal wind at 30-hPa.	Suppressed TC conditions tend to occur in east phases, enhanced during west phases. Camango and Sobel (2010) found that the QBO was not well correlated to Atlantic TCs after 1983.	Gray et al. 1994, Camango and Sobel 2010
SPUWIND	South Central Tropical Pacific 200-hPa zonal wind for region between 0°S-15°S, 150°E-120°W.	Anomalous upper-level westerly zonal winds in the south-central tropical Pacific are typically associated with ongoing La Nina conditions and a stronger Walker Circulation. Anomalously strong upper-level westerly winds would indicate a reduced chance to transition to El Nino. Positive values are associated with favorable Atlantic hurricane conditions.	Klotzbach et al. 2019.

Tropical Cyclone Output

Tropical cyclone counts used as the deep learning model predictand for 1950-2018 are from the hurricane dataset (HURDAT) maintained by NOAA's National Hurricane Center (NHC).

Climatology (1981-2010)

Season Type	Mean	Range of Named storms	Mean	Range of Hurricanes	Mean	Range of Major Hurricanes
Above-Normal	16.5	12 to 28	9.7	7 to 15	4.8	3 to 7
Near-Normal	12.3	10-15	6.3	4 to 9	2.3	1 to 4
Below-Normal	6.7	4 to 9	3.3	2 to 4	1.0	0 to 2
All Seasons	12.1	4 to 28	6.4	2 to 15	2.7	0 to 7

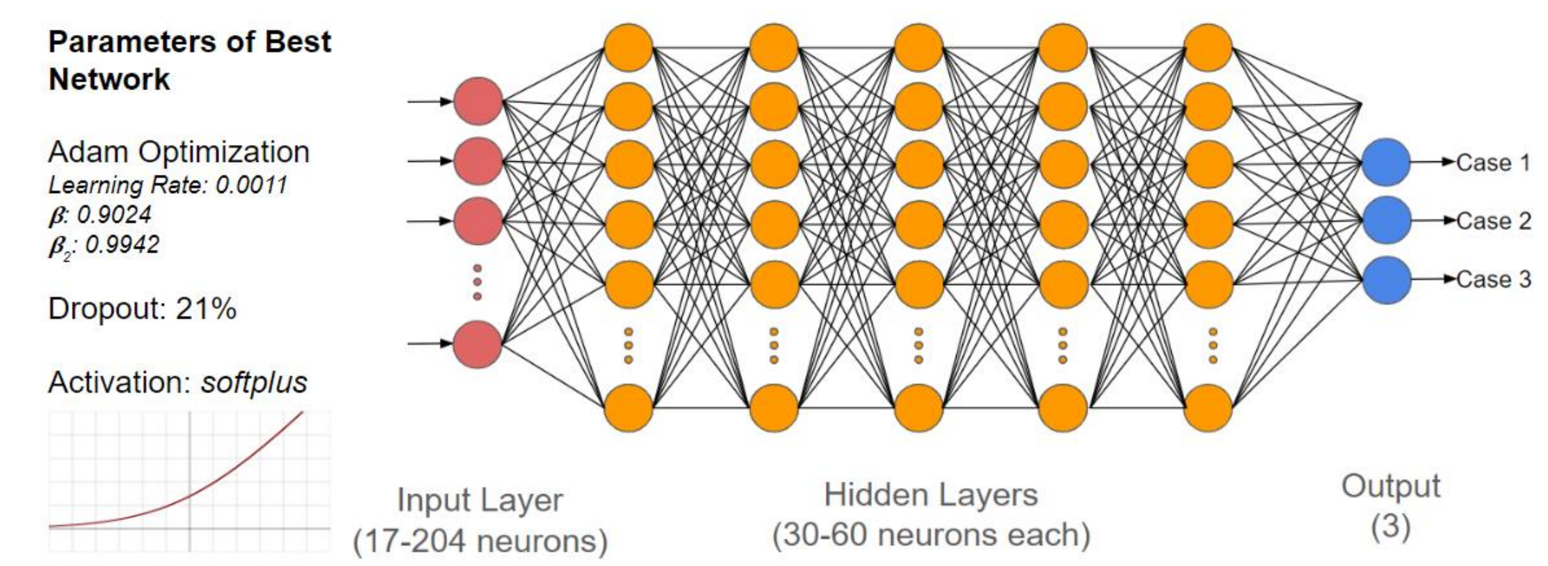


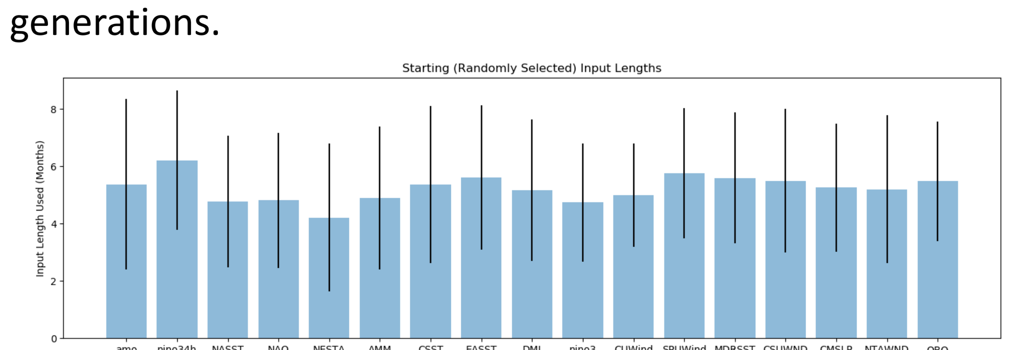
Categorical Forecast BINS

	Storm Type			1951-2018 Occurences		
	NS	H	MH	NS	H	MH
BIN 1	0-8	0-4	0-1	20	22	19
BIN 2	9-15	5-8	2-3	38	33	31
BIN 3	≥ 16	≥ 9	≥ 4	9	11	18

Network Hyperparameter Search

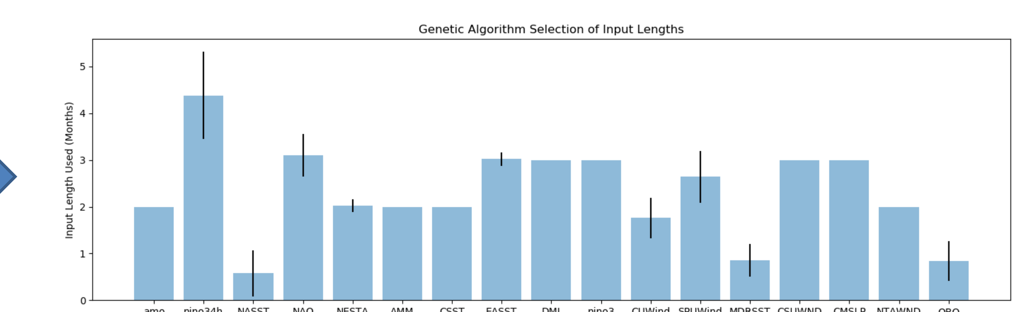
We employ a genetic algorithm (GA) to tune the hyperparameters of a fully connected neural network (NN) for seasonal hurricane forecasting. Hyperparameters set by the genetic algorithm include the number and width of hidden layers, the learning rate, β and β_2, the dropout ratio, and the activation function. The GA also optimizes the number of months of data for each input. Parameters used for the GA include a population size of 50, and 20 generations.





Network Input Layer (Default)

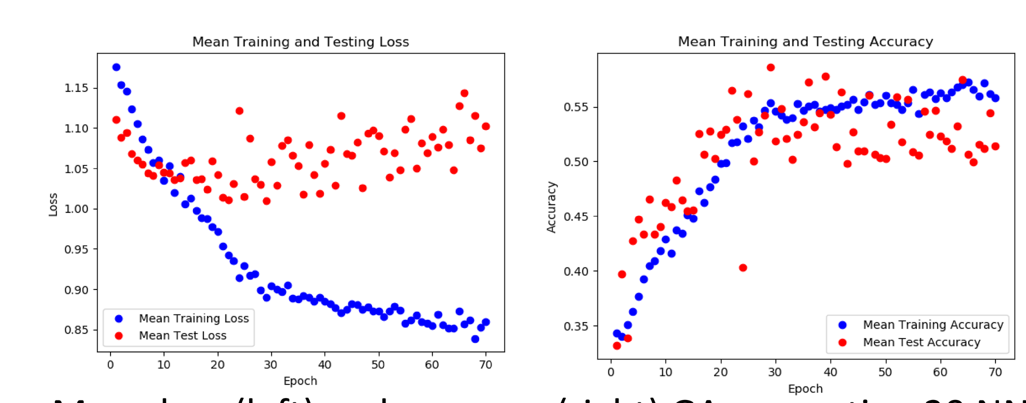
GA



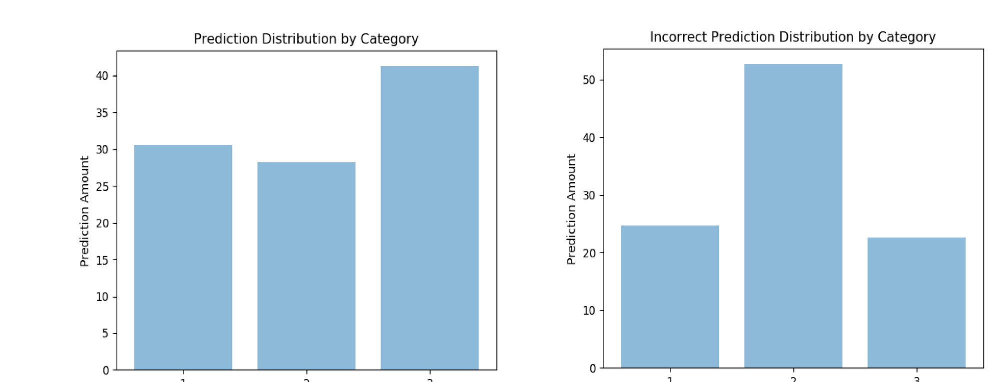
Network Input Layer (Selected by GA)

Results

This work demonstrates the potential of neural networks to integrate information from 17 predictors to make a seasonal forecast on June 1st of named storms, hurricanes, and major hurricanes in the Atlantic.



Mean loss (left) and accuracy (right) GA generation 20 NNs



MH Prediction and Misclassification Distributions

	NS	H	MH
Best NN (%)	62.4	55.9	69.9
Pre-GA Mean NN (%)	47.0	44.2	52.4
Post-GA Mean NN (%)	56.9	48.1	61.8

Neural Network Classification Performance

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