Extratropical Transition: From Climatology to Prediction

Melanie Bieli, Adam Sobel, Suzana Camargo
Jenni Evans, Tim Hall
NASA GISS Seminar, September 12, 2018
from datetime import datetime, time

say_hi()
tell_them_what_you_are_going_to_tell_them()
introduce_ET()

main_topics = [ET_global_climatology, ET_stat_prediction]
for topic in main_topics:
    motivate(topic)
    tell_them(topic)
    tell_them_what_you_told_them(topic)

while datetime.now().time() < time(14):
    question = raw_input(“Any questions?”)
    try:
        answer(question)
    except NotImplementedError:
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Extratropical Transition (ET): A Primer
ET: A Primer

Cyclone Continuum
ET: A Primer

Tropical Cyclone

- Warm core
- Radially symmetric
- Fuel: Latent heat release
**Cyclone Continuum**

**Tropical Cyclone**
- Warm core
- Radially symmetric
- Fuel: Latent heat release

**Extratropical Cyclone**
- Cold core
- Asymmetric (“comma”)
- Fuel: Baroclinicity

Images: NOAA
ET: A Primer

Cyclone Continuum

Tropical Cyclone
- Warm core
- Radially symmetric
- Fuel: Latent heat release

Extratropical Cyclone
- Cold core
- Asymmetric (“comma”)
- Fuel: Baroclinicity

Images: NOAA
ET: A Primer

Cyclone Continuum

Extratropical Transition (ET)

Noel, 2007

Tropical

Extratropical

Nov. 2, 0015 UTC

Nov. 2, 1530 UTC

Images: NOAA
Why do we care?

St. John's after Igor (2010)
Image: The Telegram

New York City after Sandy (2012)
Image: The Telegram
Global ET Climatology

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<th>Interlude: CPS</th>
<th>ET: Global Climatology</th>
<th>ET: Statistical Prediction</th>
</tr>
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</table>

From Case Studies...
From Case Studies...

Ophelia (2017)

IR loop of Ophelia. Eumetsat/Wetterzentrale
...to Basins...

**ET in the North Atlantic**

...to a Global Climatology of ET
...to a Global Climatology of ET
Interlude: Measuring “(Extra)tropicalness” in the Cyclone Phase Space
Method: ET in the Cyclone Phase Space

- \( B < 10 \): symmetric
- \( B > 10 \): asymmetric

- \( -V_T > 0 \): warm core
- \( -V_T < 0 \): cold core
ET in the Cyclone Phase Space

**ET Onset**

**ET Pathway 1:** $B \rightarrow V_T$

**ET Pathway 2:** $V_T \rightarrow B$

**ET Pathway 3:** direct

**ET Completion**

- $B < 10$: symmetric
- $B > 10$: asymmetric
- $-V_T > 0$: **warm** core
- $-V_T < 0$: **cold** core
ET in the Cyclone Phase Space

**ET Pathway 1:** \( B \rightarrow V_T \) asymmetric

**ET Pathway 2:** \( V_T \rightarrow B \)

**ET Pathway 3:** direct

\( B < 10 \): symmetric  \( B > 10 \): asymmetric  \(-V_T > 0\): warm core  \(-V_T < 0\): cold core
ET in the Cyclone Phase Space

- **ET Pathway 1:** \(B \rightarrow V_T\)  
  - symmetric

- **ET Pathway 2:** \(V_T \rightarrow B\)
  - asymmetric

- **ET Pathway 3:** direct

**ET Onset**

**ET Completion**

- \(B < 10\): symmetric
- \(B > 10\): asymmetric
- \(-V_T > 0\): **warm** core
- \(-V_T < 0\): **cold** core
B < 10: symmetric  B > 10: asymmetric  -V_T > 0: warm core  -V_T < 0: cold core

ET in the Cyclone Phase Space

ET Pathway 1:  B $\rightarrow$ V_T  
ET Onset: asymmetric  
ET Completion: cold core

ET Pathway 2:  V_T $\rightarrow$ B  
ET Onset: cold core  

ET Pathway 3:  direct
**ET in the Cyclone Phase Space**

- **ET Pathway 1:** $B \rightarrow V_T$
  - **ET Onset:** asymmetric
  - **ET Completion:** cold core

- **ET Pathway 2:** $V_T \rightarrow B$
  - **ET Onset:** cold core
  - **ET Completion:** asymmetric

- **ET Pathway 3:** direct

- $B < 10$: symmetric
- $B > 10$: asymmetric
- $-V_T > 0$: warm core
- $-V_T < 0$: cold core
**ET in the Cyclone Phase Space**

<table>
<thead>
<tr>
<th>ET Onset</th>
<th>ET Completion</th>
</tr>
</thead>
<tbody>
<tr>
<td>B → $V_T$</td>
<td>cold core</td>
</tr>
<tr>
<td>asymmetric</td>
<td>asymmetric</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ET Pathway 1:</th>
<th>ET Pathway 2:</th>
</tr>
</thead>
<tbody>
<tr>
<td>B → $V_T$</td>
<td>$V_T$ → B</td>
</tr>
<tr>
<td>asymmetric</td>
<td>cold core</td>
</tr>
<tr>
<td></td>
<td>asymmetric</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ET Pathway 3:</th>
</tr>
</thead>
<tbody>
<tr>
<td>direct</td>
</tr>
</tbody>
</table>
Data: Best Tracks (1979-2017), Reanalyses
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Global ET Climatology: Results
ET Fraction

- **best-track labels**
- **CPS, JRA-55**
- **CPS, ERA-Interim**

<table>
<thead>
<tr>
<th>Region</th>
<th>ET Fraction [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAT</td>
<td>50</td>
</tr>
<tr>
<td>WNP</td>
<td>45</td>
</tr>
<tr>
<td>ENP</td>
<td>30</td>
</tr>
<tr>
<td>NI</td>
<td>15</td>
</tr>
<tr>
<td>SI</td>
<td>25</td>
</tr>
<tr>
<td>AUS</td>
<td>40</td>
</tr>
<tr>
<td>SP</td>
<td>50</td>
</tr>
</tbody>
</table>
Seasonal Cycle

Introduction
ET: A Primer
Interlude: CPS
ET: Global Climatology
ET: Statistical Prediction

Seasonal Cycle Graphs:
- **NAT**
  - Monthly storm counts for NAT
- **WNP**
  - Monthly storm counts for WNP
- **SI**
  - Monthly storm counts for SI
- **AUS**
  - Monthly storm counts for AUS
- **SP**
  - Monthly storm counts for SP

Graphs show seasonal distribution of storms per year for different regions.
Landfalls of ET Storms

- Landfalls of transitioning or extratropical storms:
  - NAT: 3–4 per year, WNP: 7–10 per year
- SH: Landfalls by ET storms mainly affect AUS region, but at lower rate
Cluster Analysis
Cluster Analysis
Cluster Analysis

NAT

C1
C2
C3
C4

WNP

C1
C2
C3
C4
C5
C6
C7
Cluster Analysis

NAT

C1
C2
C3
C4

WNP

C1
C2
C3
C4
C5
C6
C7
Cluster Analysis

NAT

WNP
Cluster Analysis: WNP

ET Pathways*

<table>
<thead>
<tr>
<th>Pathway</th>
<th>C2</th>
<th>C4</th>
</tr>
</thead>
<tbody>
<tr>
<td>B → VT</td>
<td>49%</td>
<td>77%</td>
</tr>
<tr>
<td>VT → B</td>
<td>35%</td>
<td>18%</td>
</tr>
<tr>
<td>direct</td>
<td>15%</td>
<td>5%</td>
</tr>
</tbody>
</table>

* averages of JRA-55 and ERA-Interim
Cluster Analysis: NAT

ET Pathways*

<table>
<thead>
<tr>
<th>Pathway</th>
<th>C1</th>
<th>C3</th>
</tr>
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<tbody>
<tr>
<td>B → VT</td>
<td>35%</td>
<td>59%</td>
</tr>
<tr>
<td>VT → B</td>
<td>44%</td>
<td>34%</td>
</tr>
<tr>
<td>direct</td>
<td>21%</td>
<td>7%</td>
</tr>
</tbody>
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*averages of JRA-55 and ERA-Interim
Storm-by-Storm Evaluation

**JRA-55**

**ERA-Interim**

- **True positive**
- **True negative**
- **False positive**
- **False negative**

**Legend:**
- Positive: ET
- Negative: not ET

**Terms:**
- **True positive**
- **True negative**
- **False positive**
- **False negative**
Statistical Performance Measures

- F1 score (F1) and Matthews correlation coefficient (MCC): Performance measures of CPS classification into “ET storms” and “non-ET storms”, calculated by comparing with “true” best-track classification.

- Take into account the number of false positives (FP), false negatives (FN), true positives (TP), and true negatives (TN).
Statistical Performance

- Highest scores in WNP and NAT
- Lower scores in other basins, but higher for JRA-55 classifier
- Reason (?): Artificial wind profiles in JRA-55
ET Climatology: One-Slide Summary

- **Method:**
  Objective detection of ET using Cyclone Phase Space (CPS), from JRA-55 and ERA-Interim, 1979-2017

- **Global ET climatology**
  - ET fractions: about 50% in WNP and NAT, 45% in SP, rare in NI and ENP
  - Seasonal cycles in NH: peaks in early and late season; flatter in SH
  - Different pathways: Warmer SST goes along with more B → VT ETs

- **Evaluation:**
  - CPS classification agrees best with subjectively assigned best-track labels in the WNP (MCC > 0.7) and the NAT (MCC ≈ 0.6)
  - JRA-55 classifier achieves higher performance scores than ERA-Interim
  - ERA-Interim classifier has a higher false alarm rate
  - Caveat: Quality of best-tracks
Predicting ET Using Statistical Learning
Motivation

Individual characteristics + environmental conditions → Transition?

Image: John Atkinson, Wrong Hands
Machine Learning vs. Statistics

Machine Learning

Traditional Statistics

Images: Randall Munroe (www.xkcd.com), Matthew Freeman
Machine Learning vs. Statistics

Machine Learning

Traditional Statistics
Machine Learning vs. Statistics

- Branch of AI

Machine Learning

Traditional Statistics
Machine Learning vs. Statistics

- **Machine Learning**
  - Branch of AI
  - Predictions

- **Traditional Statistics**
Machine Learning vs. Statistics

- Branch of AI
- Predictions
- Data-oriented
Machine Learning vs. Statistics

- Machine Learning
  - Branch of AI
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  - Concern for overfitting but not model complexity per se

- Traditional Statistics
Machine Learning vs. Statistics

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Traditional Statistics
- Probability theory
Machine Learning vs. Statistics

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- Inferences about population from sample data
Machine Learning vs. Statistics

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Machine Learning vs. Statistics

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- Parameter interpretability
Machine Learning vs. Statistics

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Statistical Learning
Questions for the Gray Box:

Given a set of features describing the cyclone and its environment, can a statistical model...
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- ... assess the relative importance of different features for a cyclone’s probability of being / becoming extratropical?
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Given a set of features describing the cyclone and its environment, can a statistical model...

- ... assess the relative importance of different features for a cyclone’s probability of being / becoming extratropical?
- ... predict if the cyclone will be tropical or extratropical at lead times of 24h, 48h, etc.?
The Gray Box: Logistic Regression with Lasso
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Goal: Assign a data sample \( x \) to class 1 (EX) or 0 (not EX)
The Gray Box: Logistic Regression with Lasso

Goal: Assign a data sample $x$ to class 1 (EX) or 0 (not EX)

$$h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$$

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_n \end{bmatrix}$$

$$x = \begin{bmatrix} 1 \\ x_1 \\ \vdots \\ x_n \end{bmatrix}$$
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weights, coefficients

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weights, coefficients

$x = \begin{bmatrix} 1 \\ x_1 \\ \vdots \\ x_n \end{bmatrix}$

features

$z := \theta^T x$

$$\frac{1}{1 + e^{-z}}$$

$0.5$
The Gray Box: Logistic Regression with Lasso

Goal: Assign a data sample $x$ to class 1 (EX) or 0 (not EX)

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

weights, coefficients

features

Interpret:

$$h_\theta(x) = P(\text{class 1}|x)$$

Predict:

$$1, \ h_\theta(x) \geq 0.5$$

$$0, \ h_\theta(x) < 0.5$$
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The Gray Box: Logistic Regression with Lasso
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Goal: Prevent overfitting and select features
The Gray Box: Logistic Regression with Lasso

Goal: Prevent overfitting and select features

- “Lasso”: Regularization using L1 norm
- In general: Get $\theta_i$ by minimizing a cost function (log entropy)
- Regularization: Minimize cost under a constraint
The Gray Box: Logistic Regression with Lasso

Goal: Prevent overfitting and select features

- “Lasso”: Regularization using L1 norm
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$$J(\theta) = \frac{1}{m} \sum_{i=0}^{m} \text{Cost}(h_\theta(x^{(i)}), y^{(i)})$$
The Gray Box: Logistic Regression with **Lasso**

**Goal:** Prevent overfitting and select features

- "Lasso": Regularization using L1 norm
- In general: Get $\theta_i$ by minimizing a cost function (log entropy)
- Regularization: Minimize cost under a constraint

$$J(\theta) = \frac{1}{m} \sum_{i=0}^{m} \text{Cost}(h_\theta(x^{(i)}), y^{(i)}) + \lambda \sum_{i=1}^{m} |\theta_i|$$
The Gray Box: Logistic Regression with Lasso

Goal: Prevent overfitting and select features

- “Lasso”: Regularization using L1 norm
- In general: Get $\theta_i$ by minimizing a cost function (log entropy)
- Regularization: Minimize cost under a constraint

\[ J(\theta) = \frac{1}{m} \sum_{i=0}^{m} \text{Cost}(h_\theta(x^{(i)}), y^{(i)}) + \lambda \sum_{i=1}^{m} |\theta_i| \]

**Advantage of L1 regularization:**
Doesn’t just help avoid overfitting, but also produces sparse solutions (→ built-in feature selection)
Model Overview

Original Data

Training Data

10-fold cross validation (varying \( \lambda \))

Training Data

Validation Data

Test Data

Logistic Regression with Lasso

Model
Input

- Two models:
  - Western North Pacific (WNP)
  - North Atlantic (NAT)

- Six-hourly features from
  - Best track data
  - Reanalysis data (JRA-55)

- Predictand (‘EX’ status at \( t_0 + 24h, t_0 + 48h \), etc.) from best track data
Feature Weights

**NAT, lead time: 24h**

- lat
- B
- translation speed
- pmin
- heading angle
- $V_T^U$
- SST

**WNP, lead time: 24h**

- lat
- translation speed
- B
- pmin
- heading angle
- $V_T^U$
- SST
Performance on Test Set

Matthews Correlation Coefficient

\[ \text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \]

Brier Score Loss

\[ \text{BSL} = \frac{1}{m} \sum_{i=1}^{m} \left( h_\theta(x^{(i)}) - y^{(i)} \right)^2 \]
“Case Studies” on Test Set

Dolphin (2015)

- Predicted P('EX') at time t+24h
- True 'EX' status at time t
- True 'EX' status at time t+24h

Josephine (1996)
“Case Studies” on Test Set

Lois (1995)

Ivan (2004)

predicted $P('EX')$ at time $t+24h$
true ‘EX’ status at time $t$
true ‘EX’ status at time $t+24h$
"Case Studies" on Test Set

Helene (2006)

- Predicted P('EX') at time $t+24h$
- True 'EX' status at time $t$
- True 'EX' status at time $t+24h$
Final NHC Discussion on Sep 24 2006
The wind field is expanding as is typical of an extratropical cyclone. Microwave data and model analyses is showing a warm core...we believe this is due to a warm seclusion that is common in strong extratropical cyclones. Based on the above analyses...the extratropical transition is considered complete.
ET Prediction: One-Slide Summary

- **Method:**
  - Logistic regression with Lasso
  - 6-hourly input features: lat, translation speed, CPS parameters, SST, heading angle, pmin
  - Predictand: ‘EX’ status at $t_0 + 24h$, $t_0 + 48h$, etc.

- **Data:**
  Best-track TC data from the NAT and the WNP, JRA-55 reanalysis for environmental fields

- **Feature weights:**
  Lat and SST are most important predictors at lead time of 24 h

- **Performance:**
  - It works!
  - Metrics: Matthews Correlation Coefficient, Brier Score Loss
  - Model has skill in predicting ET at lead times up to 72 h
  - WNP model better than NAT model
Thank you!