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di Torino**



UNIVERSITÀ DEGLI STUDI DI NAPOLI  
**FEDERICO II**

## Hierarchical Time Series Analysis

# Predictive Analytics of Climate Stress Impact on the Italian Mediterranean Buffalo

Presented by  
**Mohammad Sheikh**

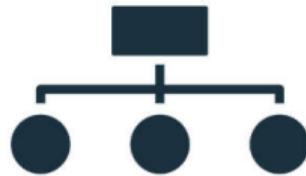
Supervisors  
**Dr. Luca Barbierato**  
**Dr. Matteo Santinello**



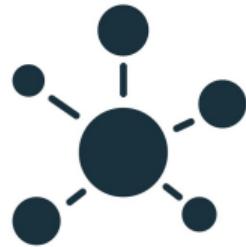
## Prediction



## Classification



## Clustering





## Prediction

- The hierarchy is a mathematical constraint.
- The numbers must add up.





## Example

How many tourists are going to visit Italy?

How about Piemonte?

How about Torino?





# Italy has 20 Regions





**We need forecasts for the  
whole of Italy, for each  
region and for each city.**





## Approach 1 : Top Down



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Forecast





**Problem : it is not accurate  
on the bottom levels**





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## Approach 2 : Bottom UP



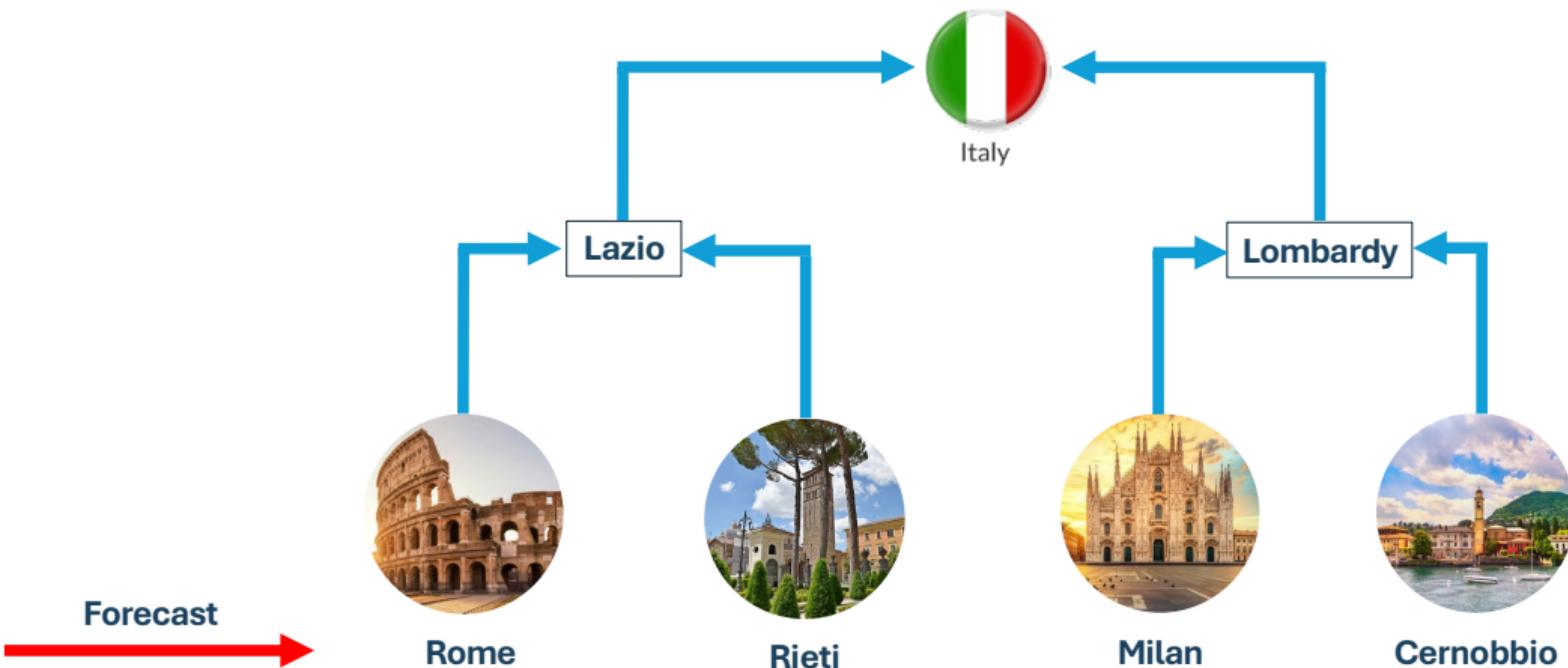
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**Problem : add up problem,  
sum of child forecasting is  
not equal to their parent**

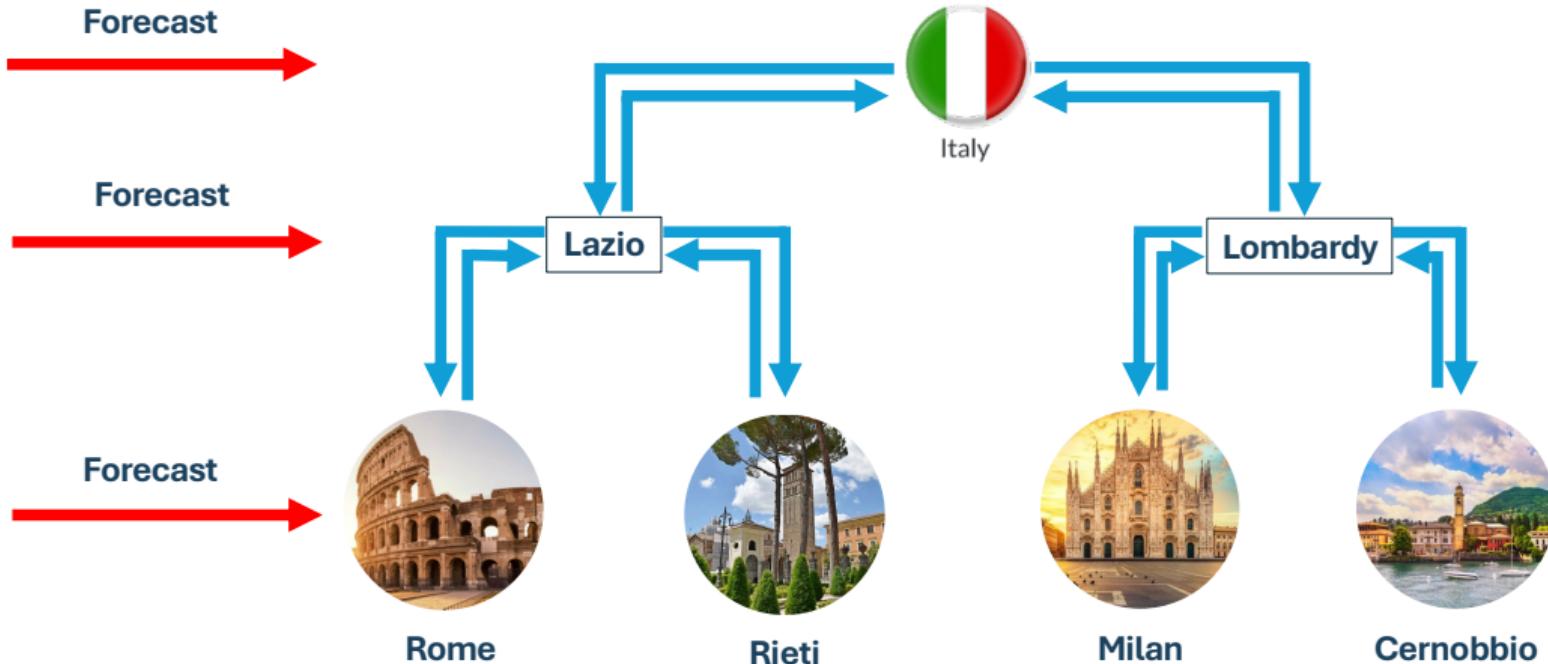




# What is optimal solution? Hierarchical Reconciliation



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## Hierarchical Reconciliation

- A model will be trained on the data[XGBoost, ...].
- Forecast on the data using current model.
- Reconcile the predicted values using statistical approaches.





## Hierarchical Reconciliation

- **MinT** : minimize the variance between reconciled values and base forecast error.
- **ERM** : minimize the error between actual values and reconciled values.





## Base model for prediction

- **XGBoost + MinT**
  - Handles Climate Data
  - Hierarchical Coherence Guaranteed
  - Highly interpretable





## Base model for prediction

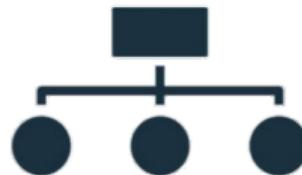
- **Neural Network- Based**
  - Handles Climate Data
  - Hierarchical Coherence NOT Guaranteed
  - Low interpretability



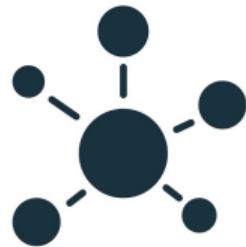
## Prediction



## Classification



## Clustering





## Classification

- The hierarchy is not a constraint to be fixed.
- Supervised task, needs to assign Labels.
- Labeling is different for each approaches.





# Approach 1

## Feature-Based





## Feature-Based Classification

- Create tabular data based on avg of past days.
- Assign label to each row as YES/NO.
- Apply a model to train on the data. [Random Forest]
- Classify based on level:
  - Animal at risk ? (Yes/No)
  - High stress event? (Yes/No)





## Feature-Based Classification : Labeling

**Goal:** Predict a "High SCC Event"

High SCC Event → SCC > 250

Animal_ID	Farm_ID	Day	Milk	SCC	THI
A-101	Farm-A	1	20	100	22
A-101	Farm-A	2	19	110	23
A-101	Farm-A	3	18	120	26
A-101	Farm-A	4	17	150	27
A-101	Farm-A	5	15	<b>260</b>	28
A-101	Farm-A	6	14	200	25





# Feature-Based Classification : Labeling

**Goal:** Predict a "High SCC Event"

Train on the new table.

Animal_ID	Day	scc_lag_1	avg THI last 3 days	Farm_ID (Hierarchical)	event_in_next_2_days (Label)
A-101	3	110	23.7	Farm-A	1 (Yes)
A-101	4	120	25.3	Farm-A	1 (Yes)
A-101	5	150	27.0	Farm-A	0 (No)





## Approach 2

# Native/Deep Learning





## Native/Deep Learning Classification

- Takes fixed-length snippet as input [3-day, 7-day]
- Assign label to each snippet based on whether high-risk event occurred in 2 days later.
- Apply a model to learn on the data. [1D-CNNs or LSTMs]





# Native/Deep Learning Classification : Labeling

**Goal:** Predict a "High SCC Event"

High SCC Event → SCC > 250

Animal_ID	Farm_ID	Day	Milk	SCC	THI
A-101	Farm-A	1	20	100	22
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A-101	Farm-A	6	14	200	25





# Native/Deep Learning Classification : Labeling

**Goal:** Predict a "High SCC Event"

High SCC Event → SCC > 250

X (The 3-Day Input Snippet)	Label
[[20, 100, 22], [19, 110, 23], [18, 120, 26]]	<b>1 (Yes)</b>
[[19, 110, 23], [18, 120, 26], [17, 150, 27]]	<b>1 (Yes)</b>
[[18, 120, 26], [17, 150, 27], [15, 260, 28]]	<b>0 (No)</b>

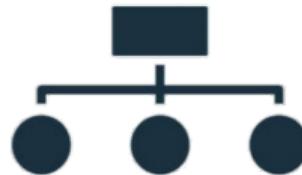
Animal_ID	Farm_ID	Day	Milk	SCC	THI
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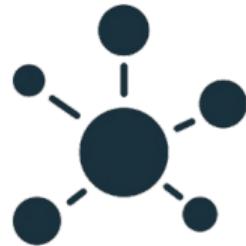
## Prediction



## Classification



## Clustering





## Clustering

- The hierarchy is not a constraint to be fixed.
- The hierarchy levels provide different "lenses" for clustering.





## Animal-Level

Clusters individual animals

- Cluster 1: "Resilient Animals".
- Cluster 2: "Vulnerable Animals".

## Farm-Level

Clusters entire farms

- Cluster A: "High-Performance Farms".
- Cluster B: "Poorly-Managed Farms".





# Approach 1

## Feature-Based





## Feature-Based Clustering

- Creates a profile for each animal/farm based on avg features.
- Applies K-means on the profiles.
- Clusters animals/farms based on different types.

### pros

- Highly interpretable and Computationally fast

### cons

- It uses Average of features instead of day-to-day data





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## Approach 2 Shape-Based



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## Shape-Based Clustering

- Extracts fixed-day data and compare with others.
- Applies dynamic Time Warping to find similarity.
- Clusters animals/farms based on behavioral patterns:
  - Cluster 1: “Fast Recovery”
  - Cluster 2: “No Recovery”





## pros

- Finds Behavioral Patterns
- Works on raw data
- Less bias

## cons

- Computationally Expensive





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