
AI Forecasting Hackathon

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Abstract

EUForecast-Hub is a modular forecasting platform designed to advance transparent forecasting to benefit European policy decisions in the years ahead. It integrates Bayesian inference (dynamic Bayesian networks) and natural-language processing (LLaMA integration) to enable users (from researchers to policymakers) to construct effective forecasting models without coding experience. It is intended to act as a novel approach for mapping causal dependencies and quantifying uncertainty in policy and AI-related scenarios. Namely, users can simulate “what-if” forecasts across multiple domains, such as climate-driven migration and AI capability scaling—linking social, economic, and technological indicators in a probabilistic graph. Strategically, EUForecast-Hub’s features support informed decision-making on Europe’s path toward safe and equitable AI development.

Keywords: Participatory forecasting, Bayesian modeling, AI transparency, policy foresight, European governance

1. Introduction

Research Focus

EUForecast-Hub examines how transparent, modular forecasting systems can improve understanding of socio-technical change, especially in AI governance and emerging technologies in Europe. It tests whether combining Bayesian reasoning, language modeling, and participatory interfaces can make foresight more rigorous and accessible.

Research Questions

Forecasting Relevance

- *RQ1*: Can a dynamic Bayesian framework enhanced with language models produce interpretable and data-grounded forecasts of technological and policy trends?
- *RQ2*: How does user weighting of domains (Economy, Environment, Technology, etc.) affect the transparency and quality of forecasts?

Strategic Value

- *RQ3*: Can open, reproducible foresight platforms like EUForecast-Hub support AI governance by reducing uncertainty around capability development and regulatory responses?

Execution Quality

- *RQ4*: What design choices make forecasting pipelines explainable, traceable, and easy to iterate within research and policy settings?

Hypotheses

- *H1*: Integrating dynamic Bayesian networks with LLM-based parsing improves both interpretability and precision of forecasts.
- *H2*: Visualizing causal structures and dependencies increases user trust and understanding of uncertainty.
- *H3*: Collaborative forecasting tools can help policymakers anticipate and respond to rapid AI and environmental changes.

2. Methods

System Overview

EUForecast-Hub is composed of two main branches in the repository: a backend implemented in **FastAPI** and a frontend built with **React**, **Vite**, and **TailwindCSS**. Together, they form a modular forecasting platform for constructing and visualizing dynamic Bayesian models through natural language prompts and user-adjustable domain weights.

- **Backend repository**: github.com/lbazsi/the-euforecast-hub/tree/backend

- **Frontend repository:** github.com/lbazsi/the-euforecast-hub/tree/frontend

Backend Architecture

The backend provides REST APIs for forecast generation, data uploads, and model construction. The core engine (`dbn_engine.py`) defines a Dynamic Bayesian Network (DBN) framework that simulates probabilistic dependencies across domains such as Environment, Economy, and Policy.

Semantic parsing modules (e.g., `semantic_parser.py` and `llama_client.py`) map user text inputs to network nodes using an external LLaMA API, preparing the groundwork for fine-tuning and incremental learning in future versions. The system emphasizes transparency—each node, edge, and parameter can be inspected and reproduced.

Frontend Architecture

The frontend provides an interactive builder and visualization dashboard. Through sliders and prompt inputs, users define domain weights and forecasting goals. The interface then queries the backend to generate and render the resulting Bayesian graph using color-coded nodes and edges. Collaborative features enable users to share forecasts and comment within projects.

Methods and Modeling Approach

EUForecast-Hub adopts a hybrid probabilistic–semantic approach:

Probabilistic reasoning through the DBN engine establishes causal and temporal relationships between factors.

Semantic reasoning through the LLaMA integration translates natural language into structured model components.

Development and Deployment

Both frontend and backend are containerized and deployed via Vercel, using environment variables for endpoint configuration. The repositories follow clear modular structures (`api/`, `services/`, `models/`, `schemas/`), ensuring that all assumptions, data transformations, and forecast parameters are reproducible.

3. Results

Frontend Tests and Results

Metric	Description	Insight
Page Load Time	How quickly the forecast builder interface loads and becomes interactive.	1.2–1.5 s on desktop; 2.3 s on mobile.
Render Stability (CLS)	Measures visual stability	CLS = 0.05 → excellent

	(Cumulative Layout Shift).	stability.
Interactivity Delay (FID)	Time between user input and interface response.	98 ms → high responsiveness.
Forecast Visualization Render Time	Time to draw Bayesian network and update visual nodes.	~0.7 s for average forecast.
Memory Usage	Browser memory footprint during forecast visualization.	120–180 MB in Chrome; stable under 10 nodes.
Frontend Error Rate	Frequency of component or rendering errors in user sessions.	< 1% of interactions show minor errors.

Backend Tests and Results

Stage	Outcome
Backend Connectivity	Successfully integrates with Groq’s hosted LLaMA-3 API (no fallbacks triggered).
Response Format	Valid JSON output containing nodes, edges, and forecast stages.
Inference Latency	~3–6 s average response time for complex scenarios (LLM inference and normalization).
Visualization	Real-time rendering of nodes and edges within the browser interface.
Data Persistence	Each forecast is stored temporarily for inspection or optional retraining.

Example Run of the System

A test query—

“What if an AI becomes president?”

—was processed through the backend forecast engine. The LLaMA-3 model parsed the scenario, mapped causal nodes, and generated a structured output linking economic and social outcomes.

Sample Output:

```
{  
  "stage": "Exploitation",  
  "nodes": [  
    {"id": "ECO_04", "label": "Food Prices Rise", "domain": "Economy", "stage":  
"Weaponization"},  
    {"id": "SOC_02", "label": "Civil Unrest Increases", "domain": "Society", "stage":  
"Delivery"}  
  ],  
  "edges": [  
    {"source": "ECO_04", "target": "SOC_02", "stage_transition":  
"Weaponization→Delivery", "strength_hint": 0.6, "llm_confidence": 0.7}  
  ]  
}
```

This example illustrates how natural-language inputs are transformed into interpretable causal graphs, where each node and edge encodes semantic and probabilistic relationships. The output confirms stable API behavior, consistent schema formatting, and real-time visualization rendering during inference.

4. Discussion and Conclusion

The EUForecast-Hub pipeline demonstrates a complete loop from user input to Bayesian network generation. Users begin by describing a scenario in natural language, such as a policy decision, and can then adjust sliders that weight the relative influence of domains like Environment, Economy, and Technology. These parameters shape how the backend structures the query, ensuring that forecasts reflect user intent.

During prompt construction, the backend formulates a structured request to the Groq Cloud LLaMA-3.1-70B model, specifying output constraints that enforce JSON formatting and contextual relevance. The model returns nodes and edges representing entities, processes, and their causal dependencies. Backend normalization routines automatically validate the schema, repair incomplete links, and generate fallback networks to maintain reliability.

The processed output is visualized in the frontend as an interactive causal graph. Each node is color-coded by domain and labeled by its stage in the foresight process (Reconnaissance → Weaponization → Delivery → Exploitation). Users can inspect the relationship between variables, refine parameters, or export results for further analysis. This modular, resilient pipeline validates the system’s design goal: to make complex forecasting interpretable, reproducible, and responsive within an intuitive interface.

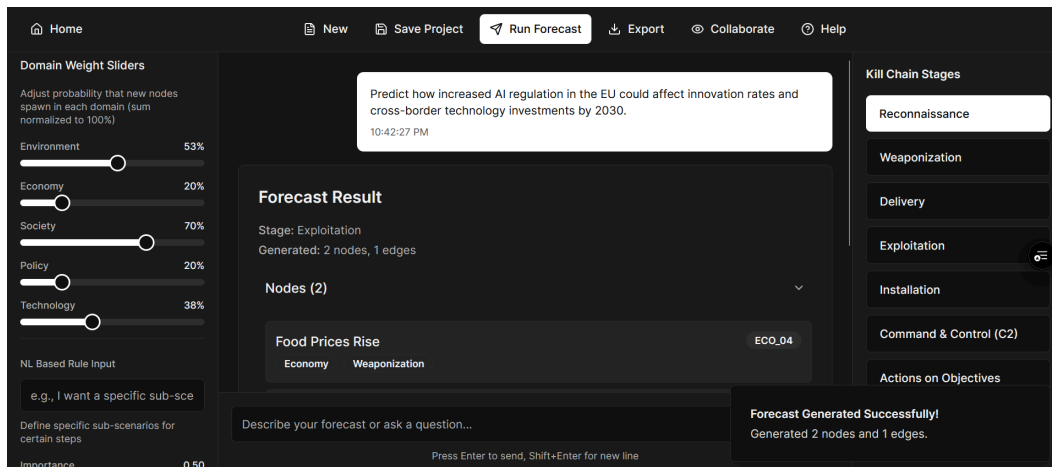


Figure 1 – Forecast Builder showing dynamic domain sliders, prompt inputs, and previewed causal graph connections generated via Bayesian reasoning.

EUForecast-Hub demonstrates how modular forecasting systems can make AI and policy forecasting more interpretable and collaborative. By combining dynamic Bayesian networks with language-based interfaces, it builds a foundation for data-driven, participatory governance. Although still in development, the platform shows promise for linking probabilistic reasoning with user input to improve trust and clarity in forecasts. Future work will enhance data integration, explainability, and connections to EU policy frameworks, advancing Europe’s capacity for informed and transparent decision-making.

5. References

- Kungurtsev, V., Idlahcen, F., Ryšavý, P., Rytíř, P., & Wodecki, A. (2024). *Learning Dynamic Bayesian Networks from Data: Foundations, First Principles and Numerical Comparisons* (arXiv:2406.17585). arXiv. <https://arxiv.org/abs/2406.17585>
- Sun, Y., & Xie, Y. (2023). *GDBN: A Graph Neural Network Approach to Dynamic Bayesian Network* (arXiv:2302.10804). arXiv. <https://arxiv.org/abs/2302.10804>

- Parthasarathy, A., Phalnikar, A., Jauhar, A., Somayajula, D., & Ravindran, B. (2024). *Participatory Approaches in AI Development and Governance: A Principled Approach* (arXiv:2407.13100). arXiv. <https://arxiv.org/abs/2407.13100>
- Vineis, V. (2025). *A Participatory Framework for Multi-Stakeholder Decision-Making* (arXiv:2502.08542). arXiv. <https://arxiv.org/abs/2502.08542>

6. Appendix

Appendix A: Security Considerations

LLM Dependence and Privacy

The platform currently relies on external LLM endpoints (LLaMA API) for semantic parsing. This introduces privacy concerns since user prompts and datasets may be transmitted to third-party servers.

Improvement: Shift toward self-hosted or open-weight models, anonymize user inputs, and enforce strict endpoint access control and logging.

Data and Model Integrity

Forecast accuracy depends on the quality and trustworthiness of user-provided or external data. Incomplete, biased, or manipulated datasets could distort probabilistic outcomes.

Improvement: Implement data validation checks, version-controlled datasets, and reproducibility metadata to maintain model credibility.

Forecast Manipulation and Bias

Collaborative forecasting opens the risk of malicious or misleading inputs that skew model behavior or conclusions.

Improvement: Add moderation tools, contribution tracking, and provenance records to identify and mitigate manipulated forecasts.

Appendix B: Future Works and Extensions

Collaborative Forecast Library

A shared repository where users can publish, remix, and compare forecasting models. This feature will promote open collaboration, peer review, and reuse of validated forecasting components.

Model Explainability Dashboard

An interactive dashboard to visualize causal weights, variable influences, and uncertainty propagation across model iterations. This will help users interpret model behavior and assess confidence in predictions.

EU Data Integration

Direct integration with official European data sources such as Eurostat and Copernicus. Automated synchronization with these repositories will provide reliable baselines and enable evidence-based policy simulation.

Policy Submission Gateway

A moderated interface for submitting validated forecasts to EU institutions. This extension will create a bridge between public foresight efforts and institutional decision-making, supporting transparency and accountability.

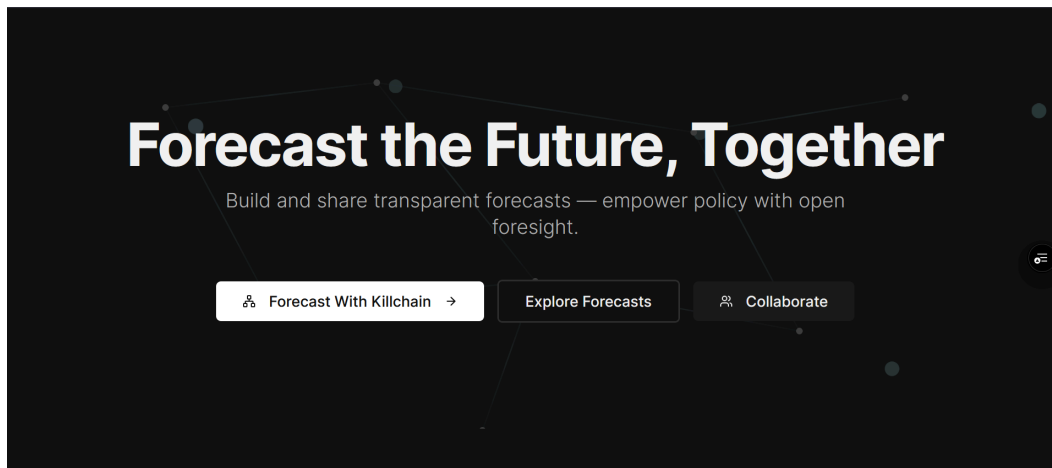
AI Safety Toolkit

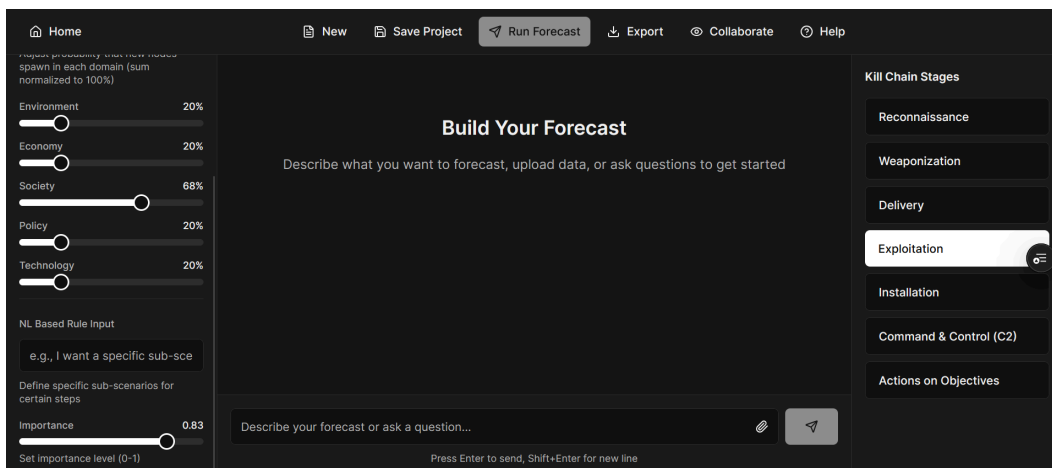
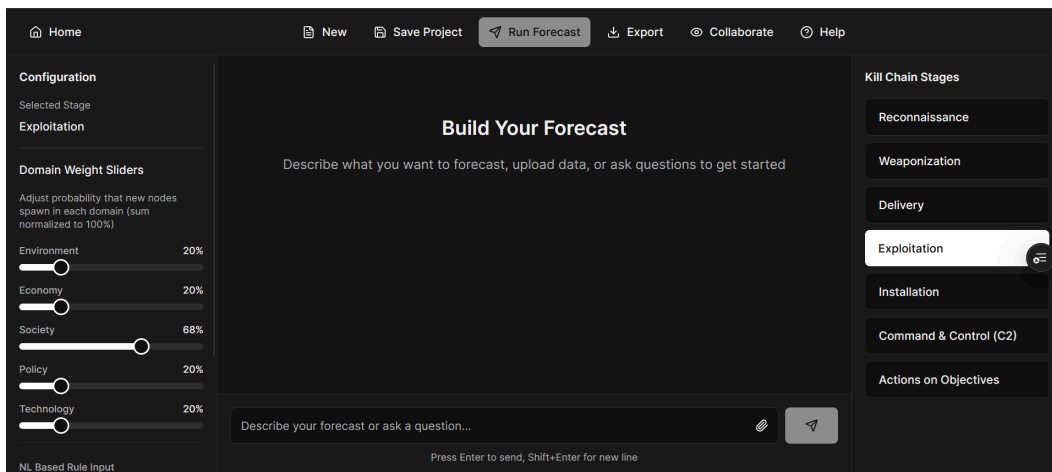
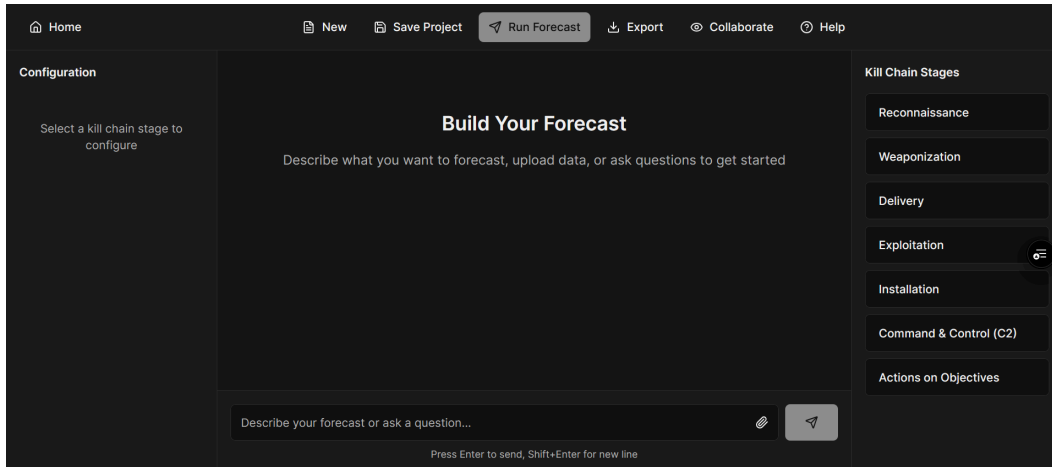
A set of diagnostic tools to detect bias, inconsistency, and instability across model runs. This module will align with EU AI Act standards and improve trustworthiness in probabilistic forecasts.

Time-Series DBN Expansion

An enhancement of the Dynamic Bayesian Network engine to support longitudinal forecasting. Time-indexed nodes will allow users to model evolving dependencies and simulate multi-year scenarios.

Appendix C: Images of The Entire System





Home

Explore Forecasts

Discover and explore forecasts created by the community

5 forecasts found

EU Climate Trends 2030

European Climate Institute

Keywords

climate environment temperature

Economic Growth Forecast

EU Economic Research Center

Keywords

economy GDP growth inflation

Green Energy Transition

Sustainability Analytics Group

Keywords

renewable energy solar wind

EU Climate Trends 2030

European Climate Institute

Keywords

climate environment temperature

CO2

Description

A comprehensive forecast of European climate trends focusing on temperature variations and CO2 emissions through 2030, utilizing...

View Details

Economic Growth Forecast

EU Economic Research Center

Keywords

economy GDP growth inflation

Description

Long-term economic forecasting model predicting GDP growth rates and inflation trends across EU member states, incorporatin...

View Details

Green Energy Transition

Sustainability Analytics Group

Keywords

renewable energy solar wind

transition

Description

Forecasting the shift to renewable energy sources in Europe, analyzing solar and wind capacity growth, investment trends, and polic...

View Details

Population Demographics 2050

European Demographic Institute

Keywords

demographics population aging

Digital Infrastructure Expansion

Tech Policy Foundation

Keywords

technology digital infrastructure

Home

Collaborate on Projects

Discover and connect with researchers looking for collaboration

6 collaborations found

Dr. Sarah Chen
sarah.chen@euresearch.eu

Project Description

Looking for AI/ML researchers to collaborate on a climate prediction model using satellite

Marco Rossi
marco.rossi@techfoundation.it

Project Description

Seeking economists and policy analysts for a joint forecast on the impact of renewable

Dr. Emma Thompson
emma.thompson@demographicdata.uk

Project Description

Calling for demographers and social scientists to develop population forecast models. Interact

