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AI-Council Canvas

- Evaluate and prioritize AI use cases by characterizing how AI can improve decision-making, augment people’s capabilities, or automate processes
- Determine which resources are needed to build and operate Artificial Intelligence
- Anticipate project risks and barriers

Projecte:

1 The task and the decision

- **Task:** Assess and predict wildfire risk levels across U.S. regions.
- **Decision:** Support emergency agencies in prioritizing **fire-prevention patrol areas** and **resource allocation plans**.
- **Current process:** Based mostly on manual experience and static reports from meteorological agencies.
- **AI improvement:** Use machine-learning models to analyze historical wildfire data and generate **dynamic risk maps** with actionable recommendations.

2 Added value proposed

- Increases accuracy and timeliness of wildfire-risk forecasting.
- Reduces human bias and resource waste.
- Provides interactive, visual risk maps for decision makers.
- Supports long-term prevention and policy planning.

3 Data

- Data is available on Kaggle (https://www.kaggle.com/datasets/firecastrl/us-wildfire-dataset) under MIT License
- All variables are standardized
- Only Data from the US
- few/none missing data

4 Judgement (decision criteria)

- False-negatives can lead to a false sense of security
  → should be avoided as much as possible
- False-positives may cause suboptimal use of resources

5 Results

- Precision-Recall-AUC, Recall, False Alarm Rate: measure how well the system predicts rare wildfire events and, and how often it raises false alarms.
- Feedback from Expert about usefulness (not feasible in this project)

6 Deployment

- **Steps to deploy:**
  1. Data pre-processing, descriptive analysis & model training
  2. Export the model
  3. Create a server/ cloud-hosted solution to fetch live data & use the model to predict risk scores
- **Tools & Infrastructure**
  - python for backend & training: pythorch, flask, pandas, …
  - optional: e.g. AWS for cloud-based processing
- **Human Agency**
  - Notifications in case of positive predictions
  - Dashboard/ Live Maps to be monitored by humans

7 Risks

- **False Predictions**: false negative & false negative
  - potential of reduced human oversight due to “over-trusting” the model
  - **Performance**: potentially limited predictability in a changing climate
- **Availability:** API-outages
- **Biased Dataset**: potential of underpredicting risks in poorly monitored or marginalized areas
- Transparency & explainability
- **Governance**: Who is responsible to evaluate predictions, and take decisions?

8 Barriers

- **Regulatory & procurement:** API licensing, data-sharing MOU, public-sector procurement timelines, liability
- **Maintenance**: Retraining the model with new data would require continuous oversight & maintenance
- **financial** (ongoing costs of server/ cloud/ training) & **hardware limitations**
- **limited domain knowledge**: difficulties interpreting or explaining certain results

Coments:

Dimension	Comentaris
Technologies	Ingestion: Python; near-real-time pulls (NWS, HRRR, RAWS) Storage & Compute: Cloud object store (Parquet), Local Machine (or Virtual Machine) for training Modeling: PyTorch, XGBoost; sequence models (TCN, lite-transformer); SHAP for explanations Knowledge rules to encode physics constraints Model registry with MLflow Github & dagshub for CI/CD collaboration
Risks	False negatives & False positives; Data Shift; Class Imbalance; Overfitting; Latency
Data	US Wildfire Dataset; near-real-time pulls (NWS, HRRR, RAWS); granularity : grid-cell or county/day
References	US Wildfire Dataset (Kaggle), Fire Weather Index (FWI); NOAA/NWS API documentation
Viability	High data and open APIs exist + ML techniques -> feasible Dependencies to training environment We start with fewer regions for POC to prove viability