Introduction:

Weather forecasting, particularly short-term temperature prediction, is crucial for various sectors including agriculture, energy, and transportation. This project aims to develop and compare two prominent models for short-term temperature forecasting: Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) neural networks. By leveraging the strengths of both traditional statistical methods and modern deep learning techniques, we seek to improve the accuracy and reliability of temperature predictions.

Now, let's address Heitmeier’s questions:

1. What are you trying to do? Articulate your objectives using no jargon.

We aim to develop and compare two different models (ARIMA and LSTM) for predicting short-term temperature changes. Our goal is to determine which approach provides more accurate forecasts and under what conditions.

1. How is it done today? What are the limits of current practice?

Currently, both ARIMA and LSTM models are used for temperature forecasting. ARIMA models have been widely applied in meteorology due to their ability to capture linear trends and seasonality

. However, they struggle with non-linear patterns. LSTM models have shown promise in capturing complex temporal dependencies in weather data

, but can be cosssmputationally intensive and require large datasets for optimal performance.

1. What's new in your approach? Why will it be successful?

Our approach combines and compares these two methods, potentially leveraging the strengths of both. We'll also explore hybrid models that merge ARIMA and LSTM techniques

. This comprehensive comparison and potential hybridization could lead to more accurate and robust temperature forecasts.

1. Who cares?

Accurate short-term temperature forecasts are valuable for various stakeholders, including:

* Farmers for crop management
* Energy companies for demand prediction
* Transportation sectors for logistics planning
* Local governments for emergency preparedness

1. If you're successful, what difference and impact will it make? How do you measure it?

Success would mean more accurate short-term temperature forecasts, potentially improving decision-making across multiple sectors. We'll measure success using metrics like Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), comparing our models' performance against current standard forecasts

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1. What are the risks and payoffs?

Risks include:

* Computational challenges in implementing complex LSTM models
* Difficulty in obtaining sufficient high-quality data for training
* Potential overfitting of models

Payoffs include:

* Improved accuracy in short-term temperature forecasts
* Better understanding of the strengths and weaknesses of different forecasting approaches
* Potential development of hybrid models that outperform current methods

1. How much will it cost?

The primary costs will be computational resources for model training and data storage. We'll use existing R libraries and freely available weather data, minimizing additional costs.

1. How long will it take?

We estimate the project will take 4-6 months, including data collection, model development, testing, and analysis of results.

1. What are the midterm and final "exams" to check for success?

Midterm checkpoints:

* Successful data collection and preprocessing
* Implementation of basic ARIMA and LSTM models

Final evaluation:

* Comprehensive comparison of ARIMA, LSTM, and potential hybrid models
* Analysis of model performance across different weather conditions and time scales
* Presentation of findings, including visualizations of model predictions vs. actual temperatures

By addressing these questions and incorporating insights from the provided papers, we aim to conduct a thorough and impactful study on short-term temperature forecasting using ARIMA and LSTM models.