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A Machine Learning Approach to the Analysis of Real Estate Prices in the New York Metropolitan Area

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INFO 5368: Practical Applications in Machine Learning (PAML)

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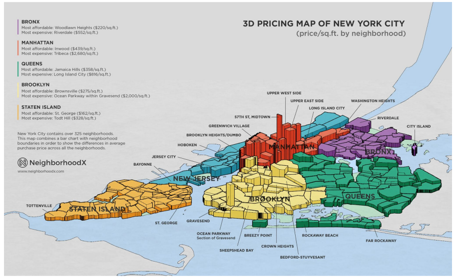
1. Introduction



Motivation:

- Tackling the problem of **predicting real estate prices in NYC**.
- Important for enhancing market transparency and informed decision-making.
- Developing an application for housing price prediction using advanced ML techniques.

Technical Focus:

- Using three ML algorithms: **Linear Regression**, **Random Forest Regression**, and **Gradient Boosting Regression**.
- These models are suited for large, complex NYC real estate data.
- Unique approach combining strengths of different algorithms for better accuracy.

Impact:

- Improves access to real estate data and pricing knowledge.
- Promotes a transparent and fair market.
- Ethical concerns: ensuring data privacy and avoiding bias reinforcement in models.

2. Background

Review of Prior Work:

- Prior research used **simpler statistical models** like linear regression.
- Advanced algorithms like Ridge Regression, Random Forest, and Gradient Boosting are now used.
  - [1] Lu et al. : Hybrid approach with Lasso regression and Gradient Boosting enhanced accuracy
  - [2] Park and Bae: Evaluated multiple ML algorithms for housing price in Fairfax County

Comparison with Proposed Work:

- Our work uses Linear Regression, Random Forest, and Gradient Boosting for NYC real estate price prediction.
- Focus on direct comparison and evaluation of multiple models.
- Leverages each model's strengths to handle NYC's market complexities.

[1] Sifei Lu, Zengxiang Li, Zheng Qin, XuLei Yang, and Rick Goh. A hybrid regression technique for house prices prediction. pages 319–323, 12 2017.

[2] Bobae Park and Jae Kook Bae. Using machine learning algorithms for housing price prediction: The case of fairfax county, virginia housing data. *Expert Systems with Applications*, 42(6):2928–2934, 2015.

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3. End-to-End ML Pipeline
3.1 Data Collection, Exploration & Processing

- **Dataset Used:** The dataset comprises property sales data from New York, NY, collected from Realtor.com via API calls. It is tailored for developing predictive models for real estate prices.
- **Data Types & Quantity:**
  - The dataset contains 10,000 records across 21 features in original. These include:
    - Categorical data: **`'status'`**, **`'style'`**, **`'city'`**, **`'county'`**
    - Numerical data: **`'zip_code'`**, **`'beds'`**, **`'full_baths'`**, **`'half_baths'`**, **`'sqft'`**, **`'year_built'`**, **`'days_on_mls'`**, **`'list_price'`**, **`'sold_price'`**, **`'assessed_value'`**, **`'estimated_value'`**, **`'lot_sqft'`**, **`'price_per_sqft'`**, **`'latitude'`**, **`'longitude'`**, **`'stories'`**.
  - This diverse set allows for comprehensive analyses of multiple aspects affecting property values.
- **Release & Source:** Data is extracted real-time covering the last 365 days from Realtor.com(May 1st, 2024), ensuring recent trends are captured for analysis.

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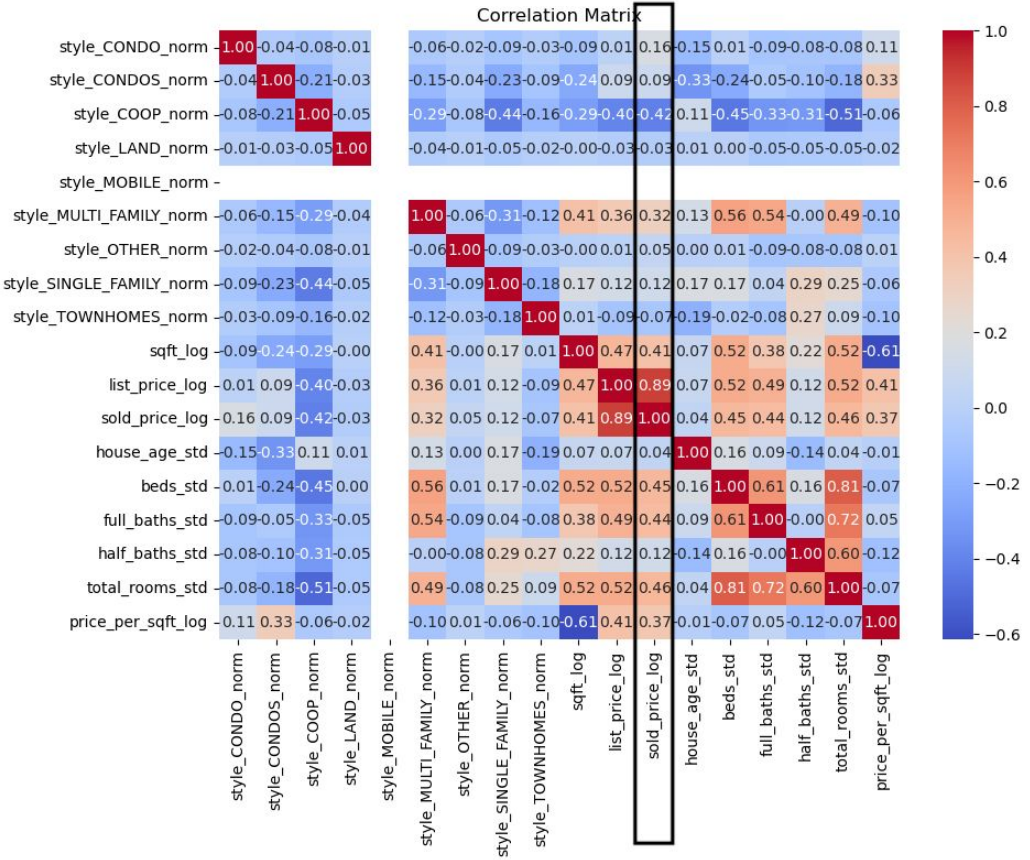
May consider these factors in model training:

```
'style_MULTI_FAMILY'
'sqft'
'list_price'
'beds'
'full_baths'
'total_rooms'
'price_per_sqft'
```



3. End-to-End ML Pipeline
3.1 Data Collection, Exploration & Processing

1. **Handling Missing Data:**
- Filling missing values in the `'half_baths'` column with zeros.
- Dropping columns with significant missing values or less relevance (e.g., `'days_on_mls'`, `'assessed_value'`, `'estimated_value'`, `'lot_sqft'`, `'stories'`).
- Filling missing values in `'sqft'` with the median value of the column.
- Using the median or mode to impute missing values in other columns like `'full_baths'`, `'beds'`, `'year_built'`, `'list_price'`, `'zip_code'`, and `'county'`.
- Geographically imputing missing latitude and longitude based on median values from the same zip code.

2. **Data Cleaning:**
- Removing or imputing outliers in geographical data, ensuring that the `'latitude'` and `'longitude'` fall within specific bounds relevant to New York City.

3. **Type Conversions:**
- Converting `'zip_code'` from float to integer after filling missing values.

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4. **Feature Engineering:**
   - **One-Hot Encoding:** The `'style'` column is transformed into multiple binary columns through one-hot encoding, ensuring that this categorical data can be used in numerical modeling.

5. **Transformation Functions Applied:**
   - **Logarithmic Transformation:** Applied to `'sqft'`, `'list_price'`, and `'sold_price'`. The new features created are `'sqft_log'`, `'list_price_log'`, and `'sold_price_log'`.
   - **Standardization:** Applied to `'house_age'`, `'beds'`, `'full_baths'`, and `'half_baths'`. The new features created are `'house_age_std'`, `'beds_std'`, `'full_baths_std'`, and `'half_baths_std'`.
   - **Normalization:** Applied to the new `'style_'` features created by one-hot encoding. New features are named like `'style_[feature]_norm'`, where [feature] is the specific style category.

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6. **New Feature Creation:**

- **Age Calculation:** A new feature `'house_age'` is created by subtracting the year_built from the current year (2024).
- **`'total_rooms_std'`:** Summarizes the total standardized counts of bedrooms and bathrooms (`'beds_std'`, `'full_baths_std'`, and `'half_baths_std'`) into a single feature, which provides a scaled representation of overall room count that could affect house valuation.
- **`'price_per_sqft_log'`:** Computes the logarithm of price per square foot by dividing `'list_price_log '` by `'sqft_log'`. This feature normalizes the price per unit area, making it easier to compare properties of different sizes.

7. **Outlier Removal:**

- Outlier removal is applied to `'sqft_log'`, `'list_price_log'`, `'sold_price_log'`, and `'price_per_sqft_log'`. Outliers are identified using the Interquartile Range (IQR) method, which defines outliers as observations that fall below Q1 - 1.5 * IQR or above Q3 + 1.5 * IQR. Removing outliers helps in reducing the impact of extreme values on the modeling process, leading to more robust and generalizable results.

3.2 Methods and Model Training

Machine Learning Techniques:

- Implemented **Linear Regression** (from scratch) to establish a baseline for performance.
- Used **Random Forest** for its ability to handle non-linear relationships.
- Applied **Gradient Boosting Regression** to leverage sequential learning and improve accuracy.

Model Inputs and Outputs:

- Inputs: `'sqft_log'`, `'beds_std'`, `'full_baths_std'`, `'total_rooms_std'`, `'zip_code'` (based on correlation matrix)
- Outputs: `'sold_price_log'`

Training and Validation Procedure:

- Split data into 80% training and 20% testing sets to evaluate model performance.
- Used Cross-validation during training to ensure robustness and reliability.

Avoiding Overfitting and Underfitting:

- Applied regularization techniques in Linear Regression to prevent overfitting.
- Tuned Random Forest and Gradient Boosting models with parameters like tree depth and number of estimators to balance bias and variance.

3.3 Model Evaluation

Evaluation Methods and Metrics:

- Predictive accuracy: **Mean Absolute Error (MAE)** and **Root Mean Squared Error (RMSE)**.
- Explanatory power: **R-squared (R^2)** to measure the proportion of the variance in the dependent variable that is predictable from the independent variables.
- Hyperparameter settings: e.g. learning rate, iterations, max depth, number of trees etc.

```python
class LinearRegressionFromScratch:
    def __init__(self, learning_rate=0.01, iterations=1000):
        self.learning_rate = learning_rate
        self.iterations = iterations
```

```python
param_grid_rf = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt', 'log2']
}
```

```python
param_grid_gb = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'subsample': [0.8, 1.0]
}
```

	Linear Regression 👎	Random Forest 👍	Gradient Boosting
RMSE	0.45	0.31	0.32
MAE	0.35	0.22	0.24
R^2	0.33	0.68	0.64

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3.4 Model Deployment

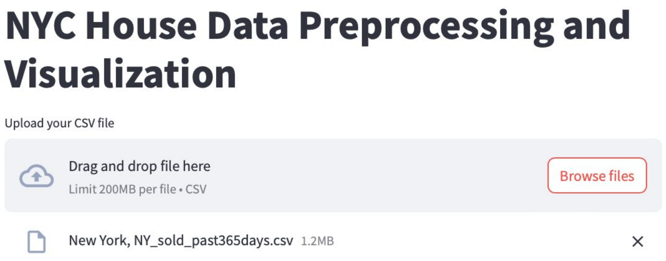
Applications of our systems includes:

- **Price Estimation:** Uses advanced algorithms (Linear Regression, Random Forest, Gradient Boosting) to predict real estate prices.
- **Market Transparency:** Supports informed decisions in NYC's real estate market.
- **Market Stability:** Aids both buyers and sellers with accurate forecasts, stabilizing the market and widening access to real estate investments.

Importance of our systems and Ethical/Societal Implications includes:

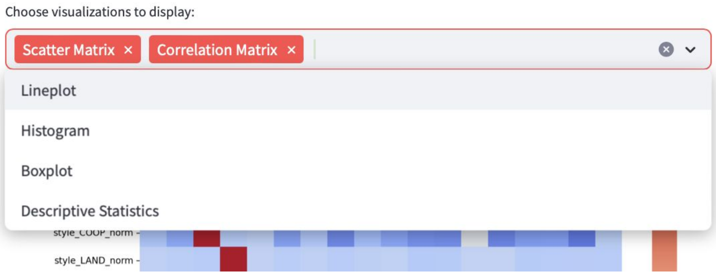
- **Democratization of Access:** Improves market transparency and equity by making complicated real estate data available.
- **Data Privacy:** Secures user data to protect personal information.
- **Bias Mitigation:** Updates and refines models to prevent perpetuating market inequities.
- **Techniques for Fairness:** Employs cross-validation and regularization to enhance model reliability and compliance with data protection laws.

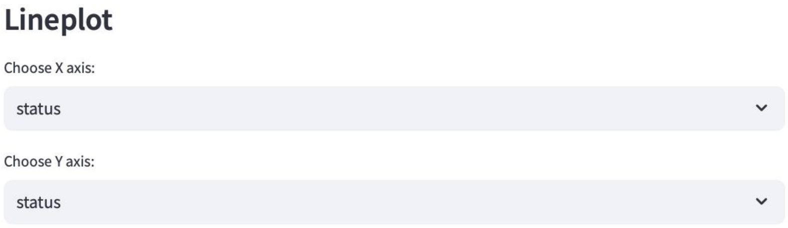
3.5 Front-End (Streamlit)



Dataset upload

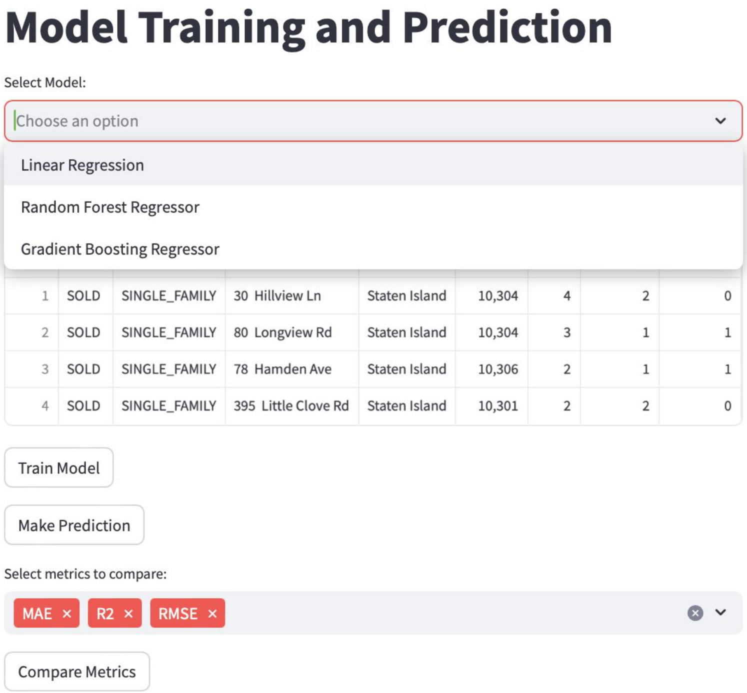
Choose visualizations to display





Choose X and Y axis

3.5 Front-End (Streamlit)



- Choose one model from select box
- Train Model button
- Make Prediction button
- Metrics select box
- Compare Metrics button

4. Results

Expected outcome in high-level:

- **Visualization Dashboard:** Features a user-friendly interface that displays insights from advanced machine learning models like Linear Regression, Random Forest, and Gradient Boosting.

- **Data Handling:** Utilizes an ETL process to manage complex NYC real estate datasets, enabling precise housing price predictions.

- **Market Insights:** Delivers in-depth market dynamics and simplifies complex data for user convenience.

- **Future Enhancements:** Plans to expand data sources and introduce more predictive models for increased accuracy and functionality.

Thank you :)