

Predict a Click!

trivago Case Study

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Data Science Workflow

- Frame the problem
- Exploratory Data Analysis
 - Missing data
 - ID characterization and uniqueness
 - In-depth feature analysis
 - Regression Analysis
 - Data representativeness
- Production Pipeline
 - Data preparation & feature engineering
 - Preprocessing
 - Training, Validation & Test



Frame the Problem

trivago – tech company providing lodging meta search services

Regression task – predict `n_clicks` of given hotel entry

- Evaluation metric – WMSE

$$wmse := \frac{1}{n} \frac{\sum_{i=0}^n w_i \cdot (\text{predictedClicks}_i - \text{observedClicks}_i)^2}{\sum_{i=0}^n w_i}$$

- ~400K entries

$$w_i := \log(\text{observedClicks}_i + 1) + 1$$

- Features – `hotel_id`, `city_id`, `content_score`, `n_images`, `stars`, `distance_to_center`, `avg_rating`, `n_reviews`, `avg_rank`, `avg_price`, `avg_saving_percent`, `n_clicks`
- Conda 4.5.11 with Python 3.6.5 on Win10 x64
 - NumPy, Pandas, Matplotlib, Seaborn, Scikit-Learn, XGBoost



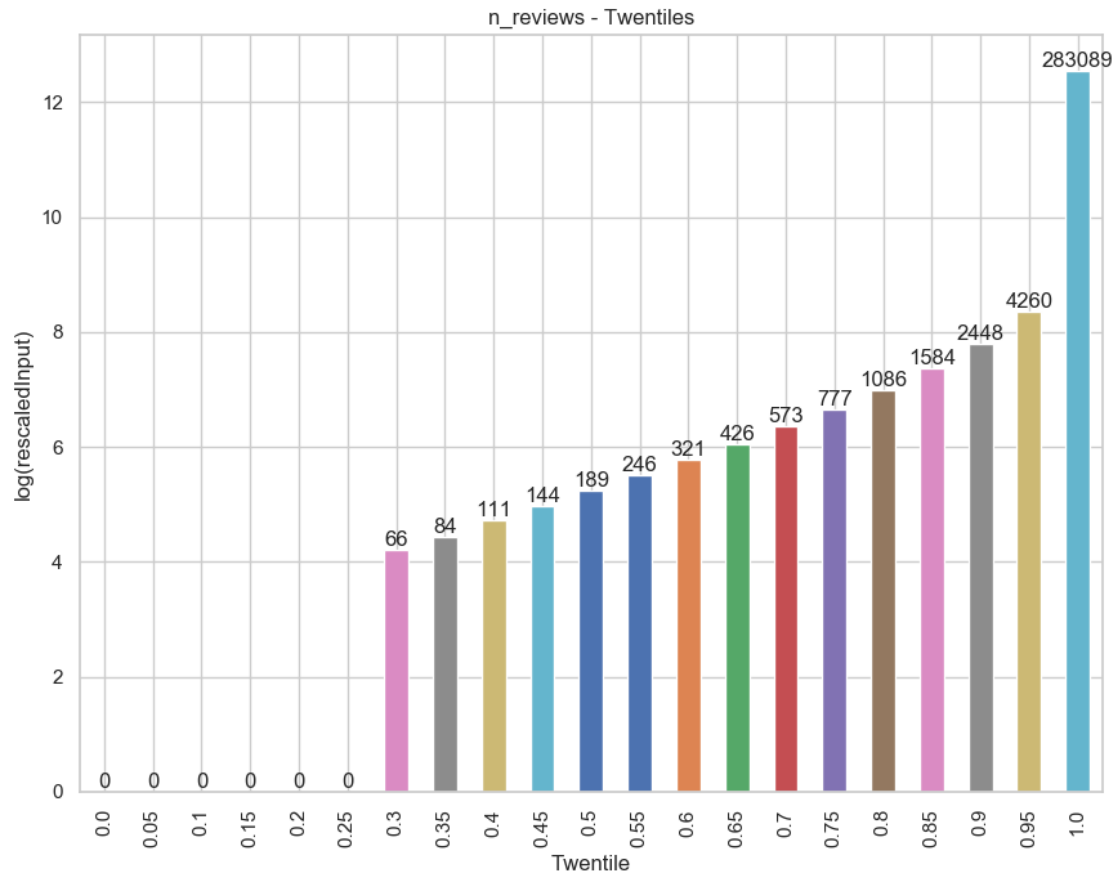
Exploratory Data Analysis (I)

- All entries have distinct `hotel_id`
- # missing values negligible excepting for `avg_rating`
 - `n_reviews=0` → `avg_rating=NaN` (Cold Start problem)
 - Naïve mean imputation / Regression imputation
- `city_id` – ~30k categories
 - One-hot encoding + shrinkage / clusterization
- ~1% of data has `n_images=-1`
- Insights from quantile/KDE/box plots
 - Extremely skewed distributions → `feature = logp1(feature)`
 - `n_clicks`, `n_images`, `distance_to_center`, `n_reviews`
 - All features have reasonable distributions



Exploratory Data Analysis (II)

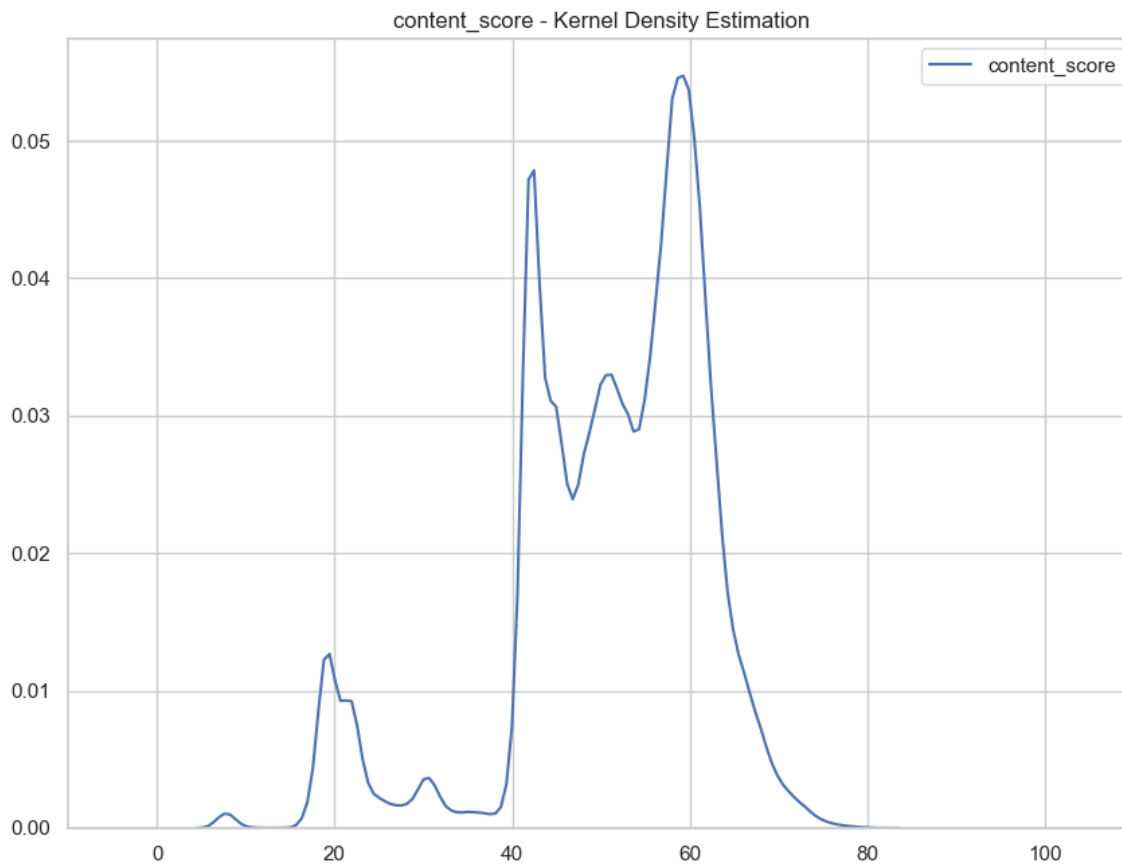
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Exploratory Data Analysis (III)

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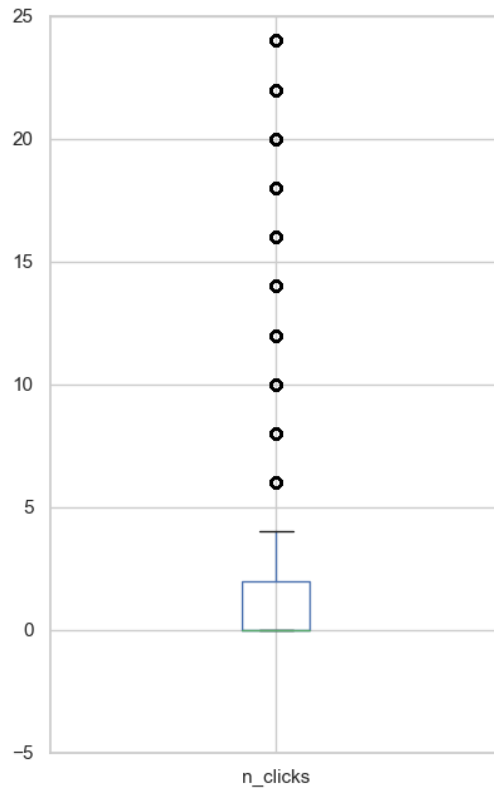
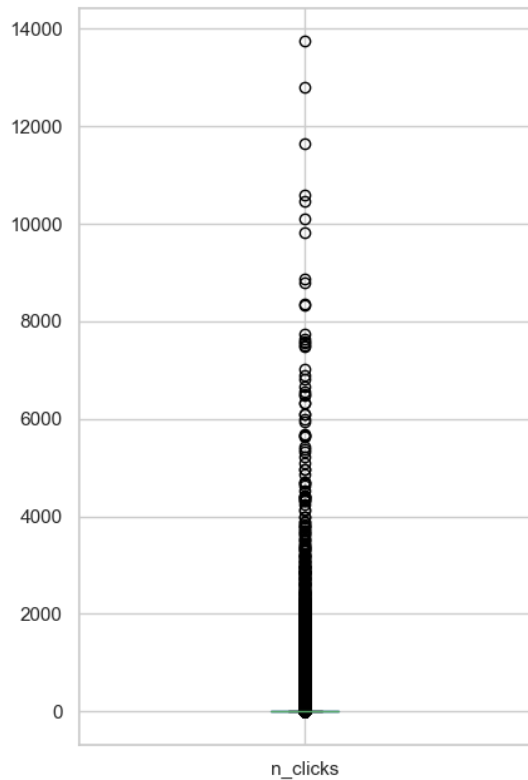




Exploratory Data Analysis (IV)

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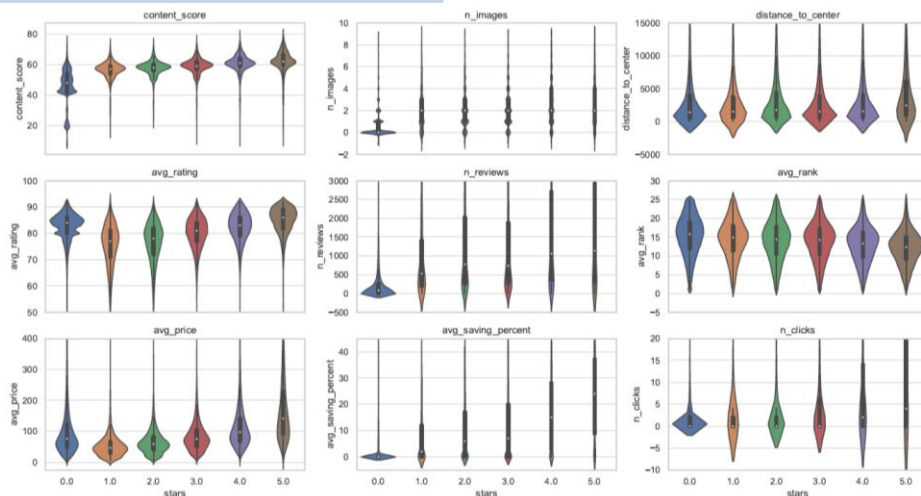
n_clicks - Box Plots





EDA – stars: the unknown feature

- Domain: integer in [0, 5]
- What does it describe?
 - Violin plots → hotel stars rating
 - content_score, avg_price, avg_rating grow with stars
 - avg_rank decreases with stars
- What is a 0-star hotel?
 - Violin plots & trivago website → hostels & apart-hotels
 - Consistently lower content_score, n_reviews
 - Most of 0-star entries have 0 n_images and avg_saving_percent
- Solutions: categorical / numerical+regression imputation

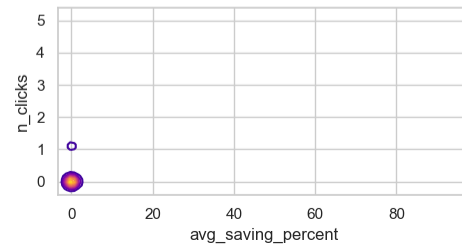
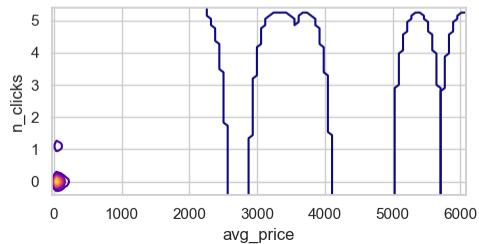
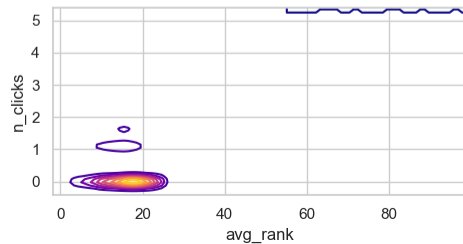
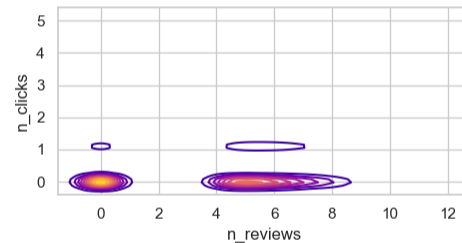
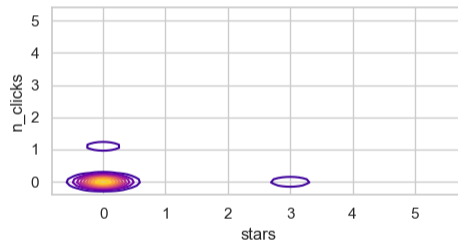
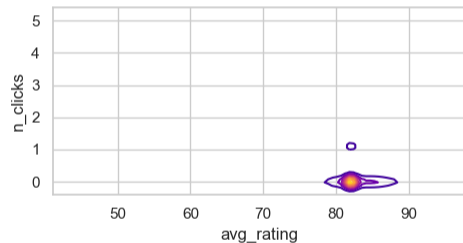
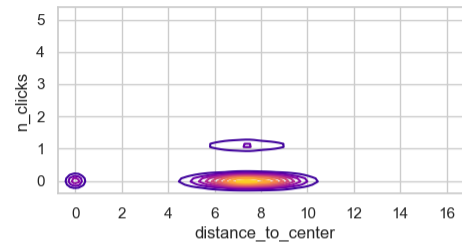
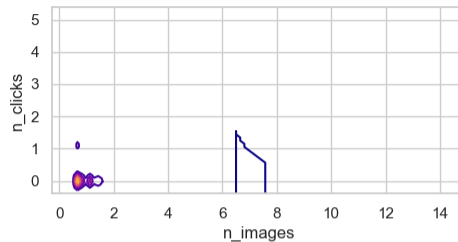
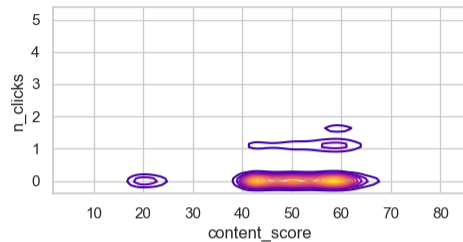




EDA – Bivariate KDE

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Bivariate Kernel Density Estimation

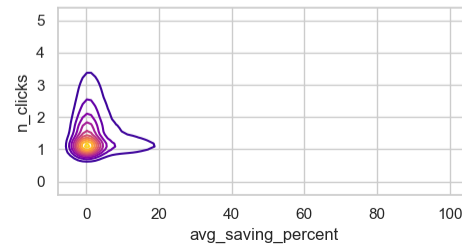
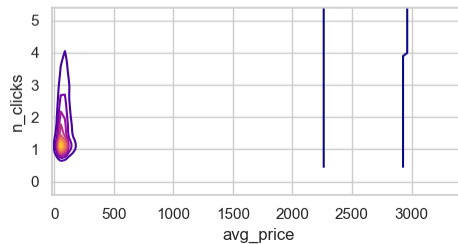
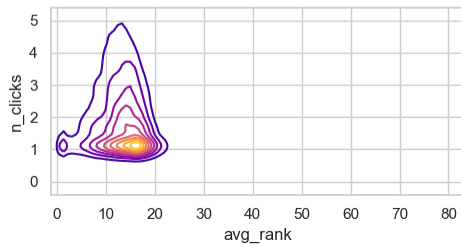
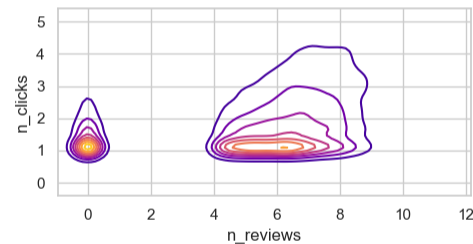
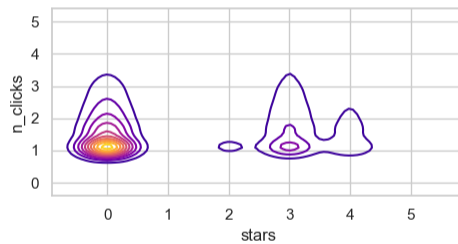
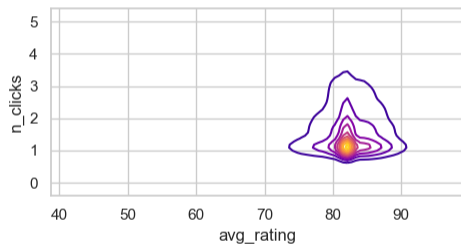
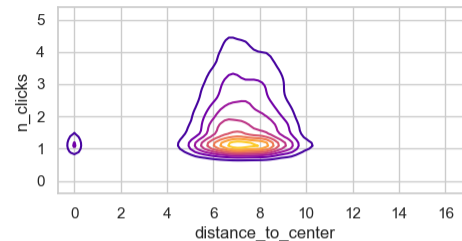
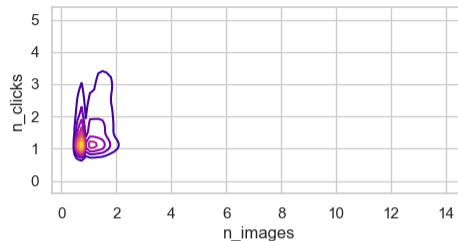
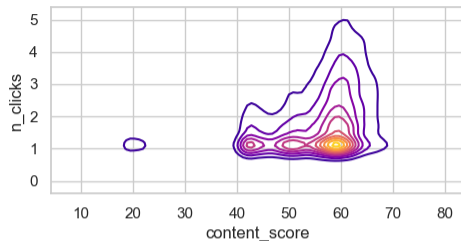




EDA – Bivariate KDE ($n_clicks > 0$)

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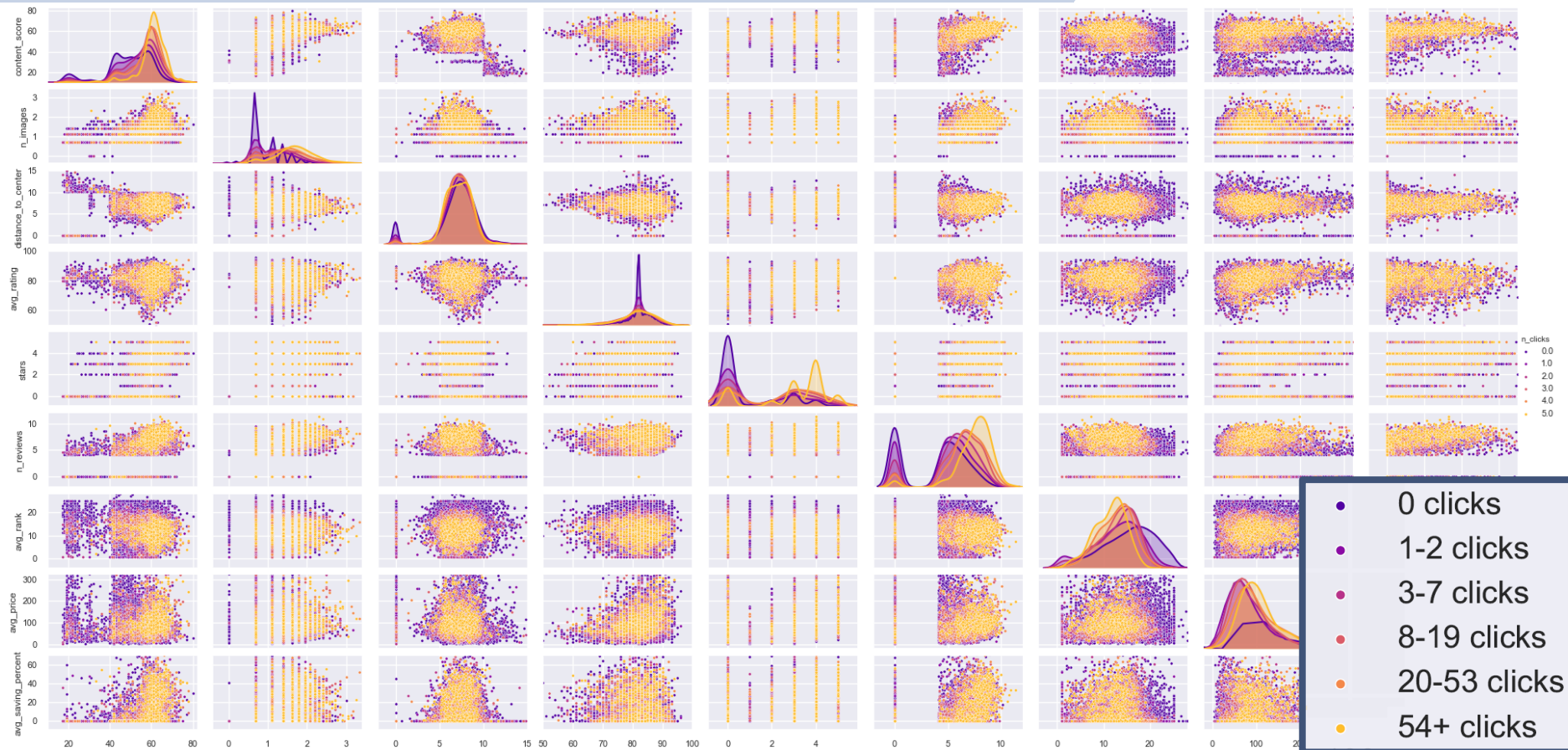
Bivariate Kernel Density Estimation - $n_clicks > 0$





EDA – log-Discretized Pairplots

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Experimental Framework

- Training & Validation / Test – 90/10 randomized split
- Experimental reproducibility (random_state=0)
- Preprocessing
 - Production-ready: type cast, NaN dropping/handling, domain checks
 - Min Max Scaler / Max Abs Scaler
 - One-Hot Encoding / Truncated SVD
- Training
 - 5-fold randomized Cross-Validation
 - Grid search / Randomized search
 - XGBoost with WMSE-based Early Stopping
 - Statistical significance assessment: Wilcoxon Test

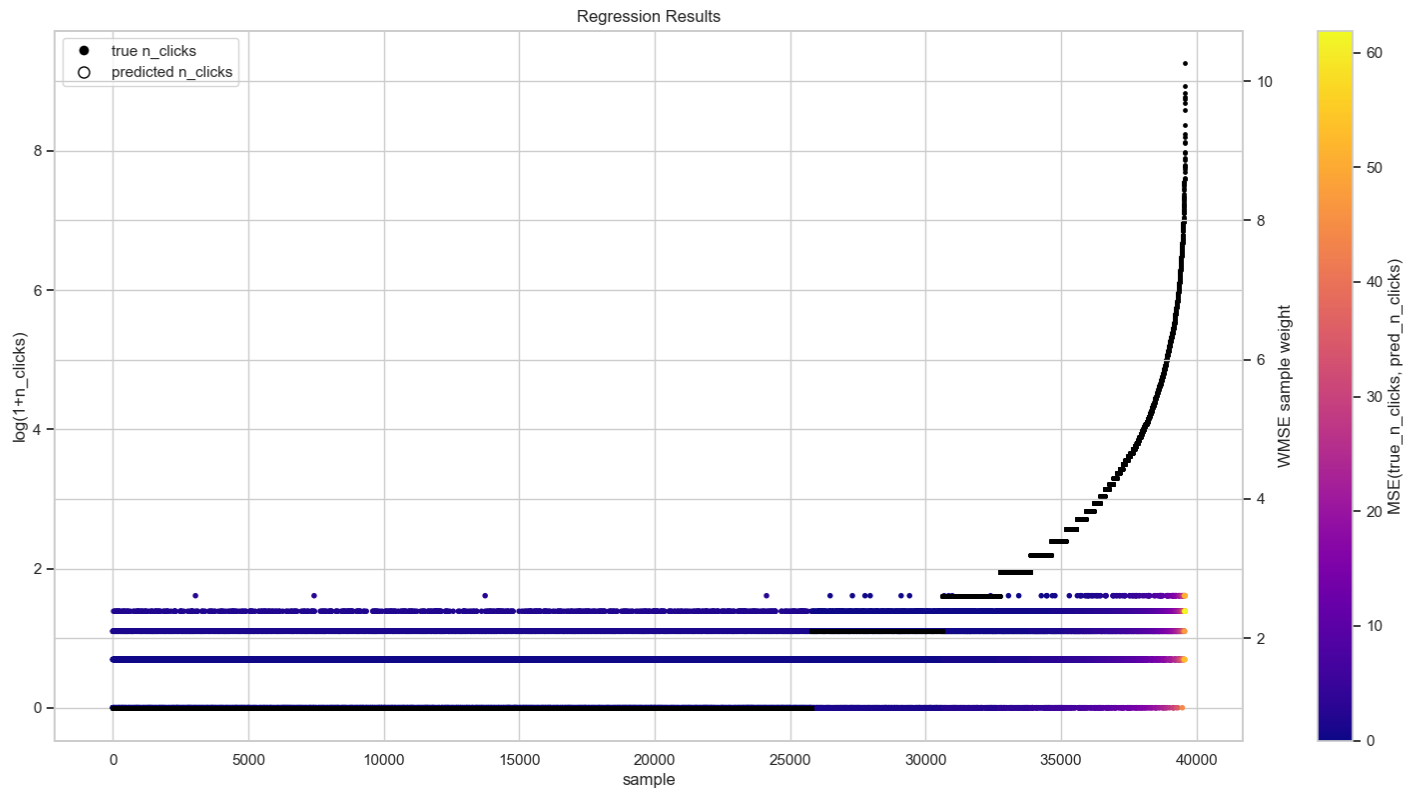


ElasticNet, PolyRegression, SVR

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WMSE \approx 2.24

Random Baseline WMSE = 2.24



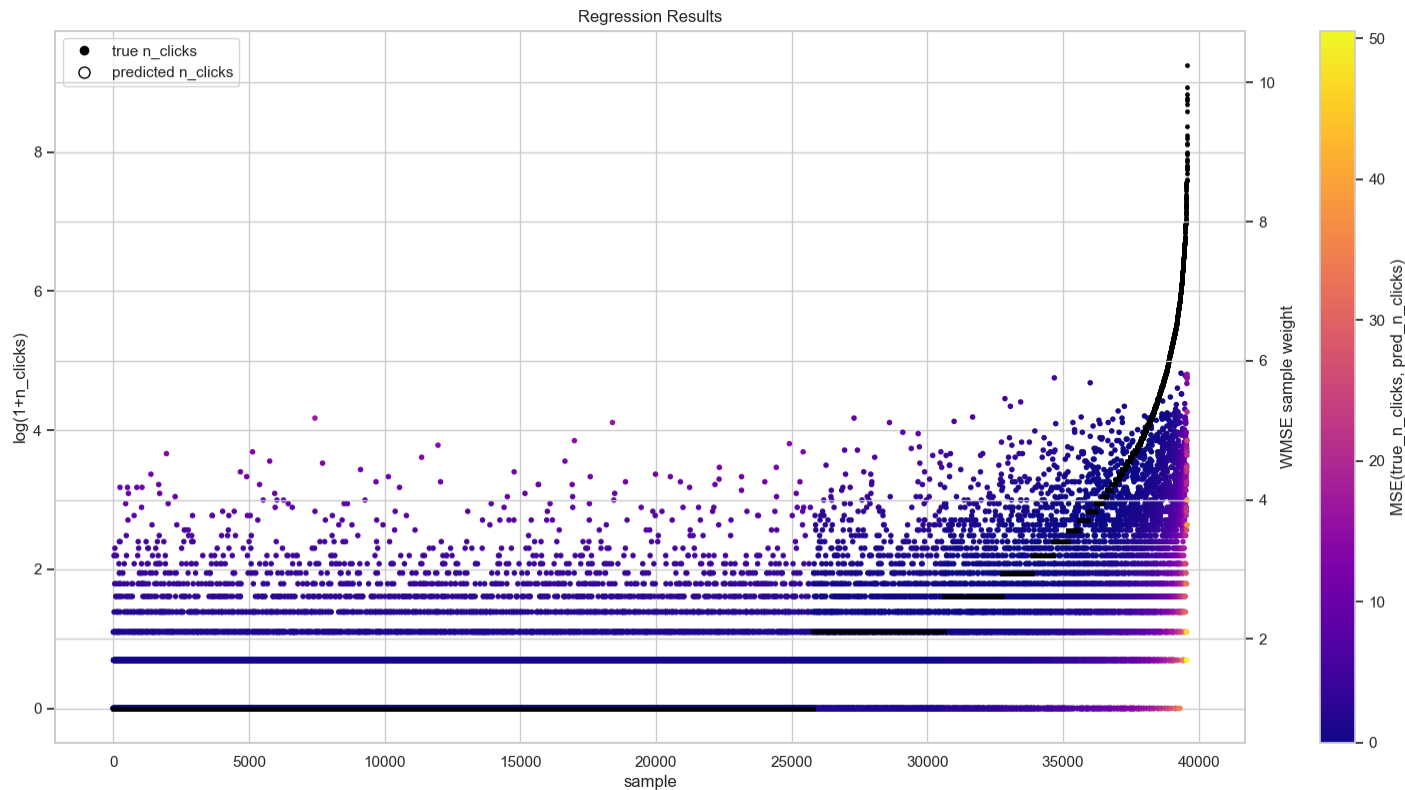


Random Forest

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WMSE = 2.20

Random Baseline WMSE = 2.24



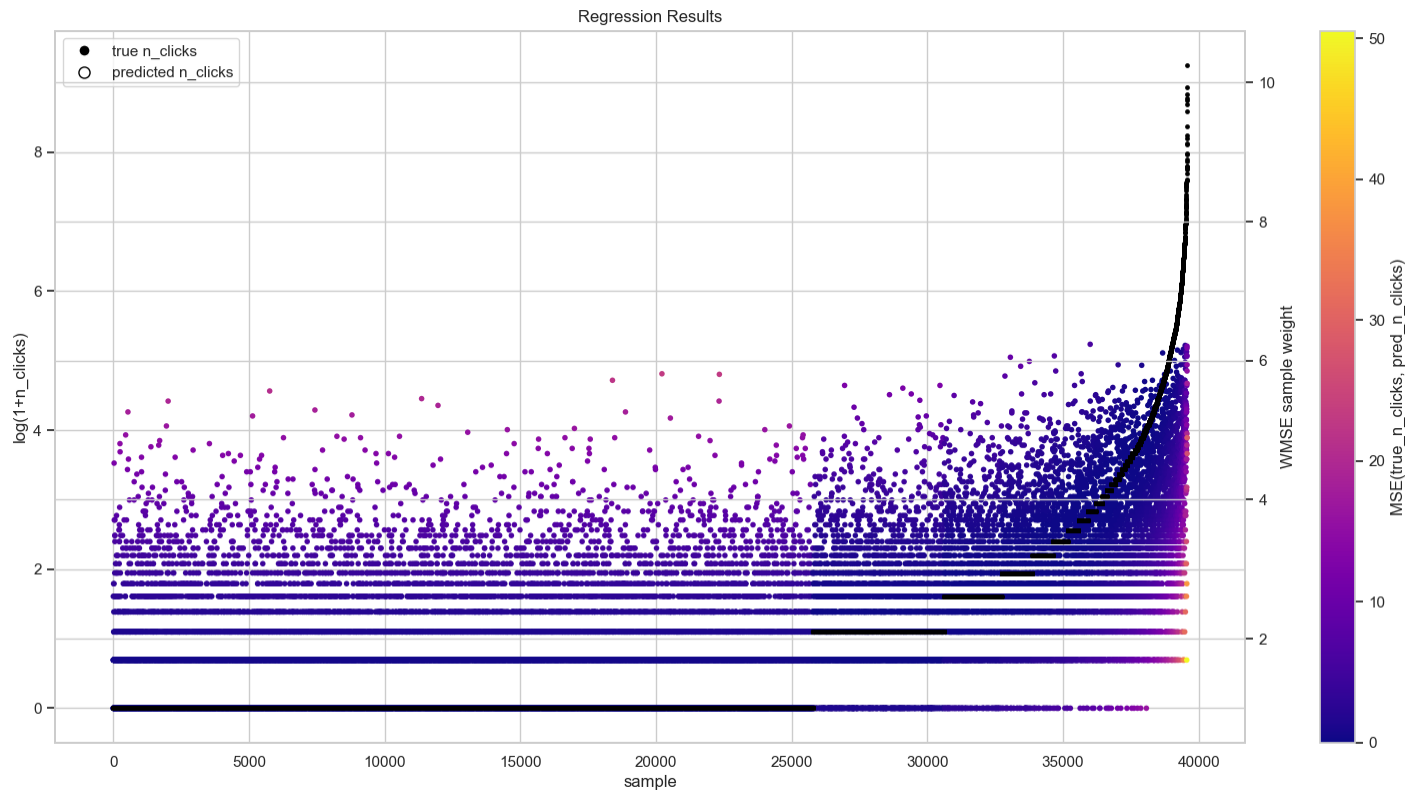


Random Forest + Weighted Oversampling

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WMSE = 2.12

Random Baseline WMSE = 2.24



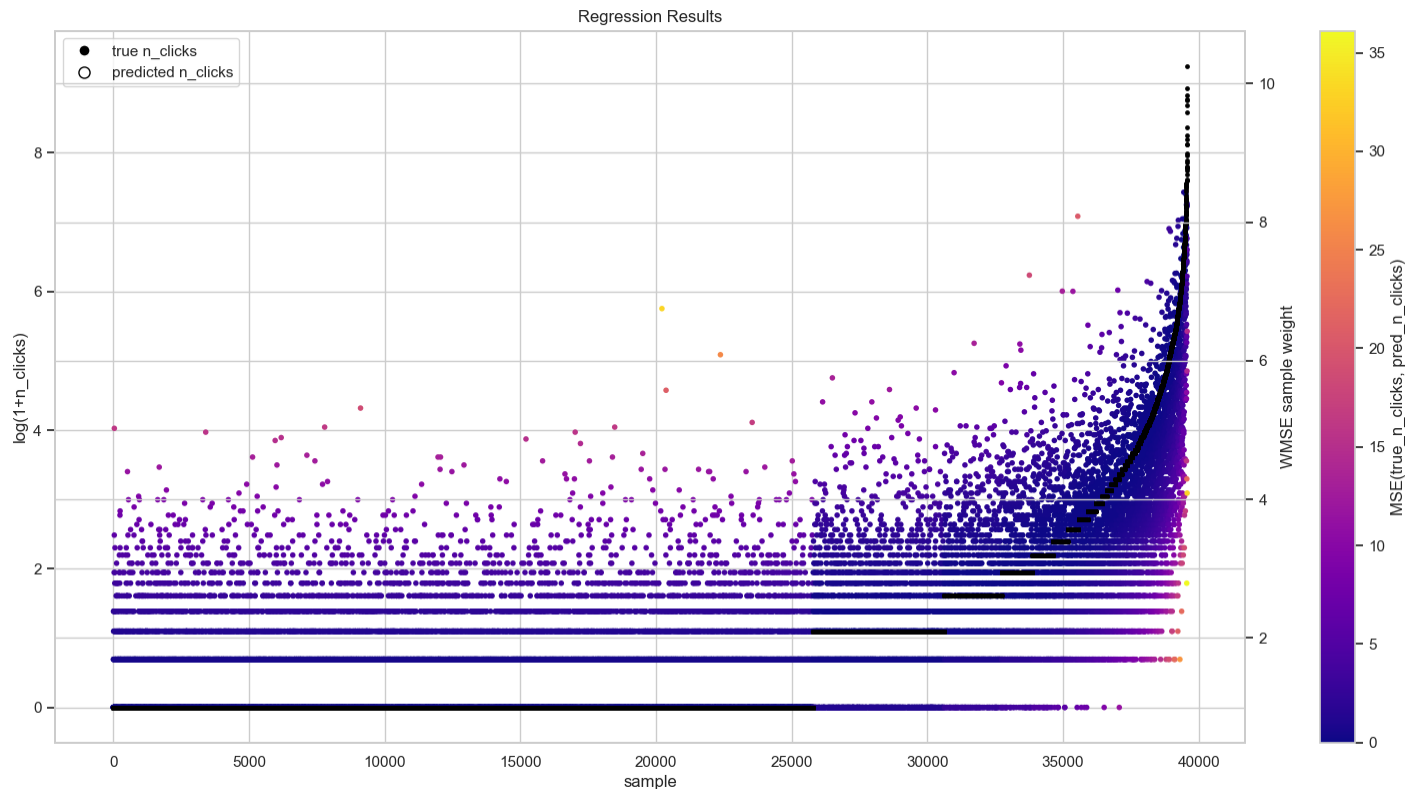


XGBoost + Weighted Oversampling

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WMSE = 1.66

Without WO, WMSE = 1.74



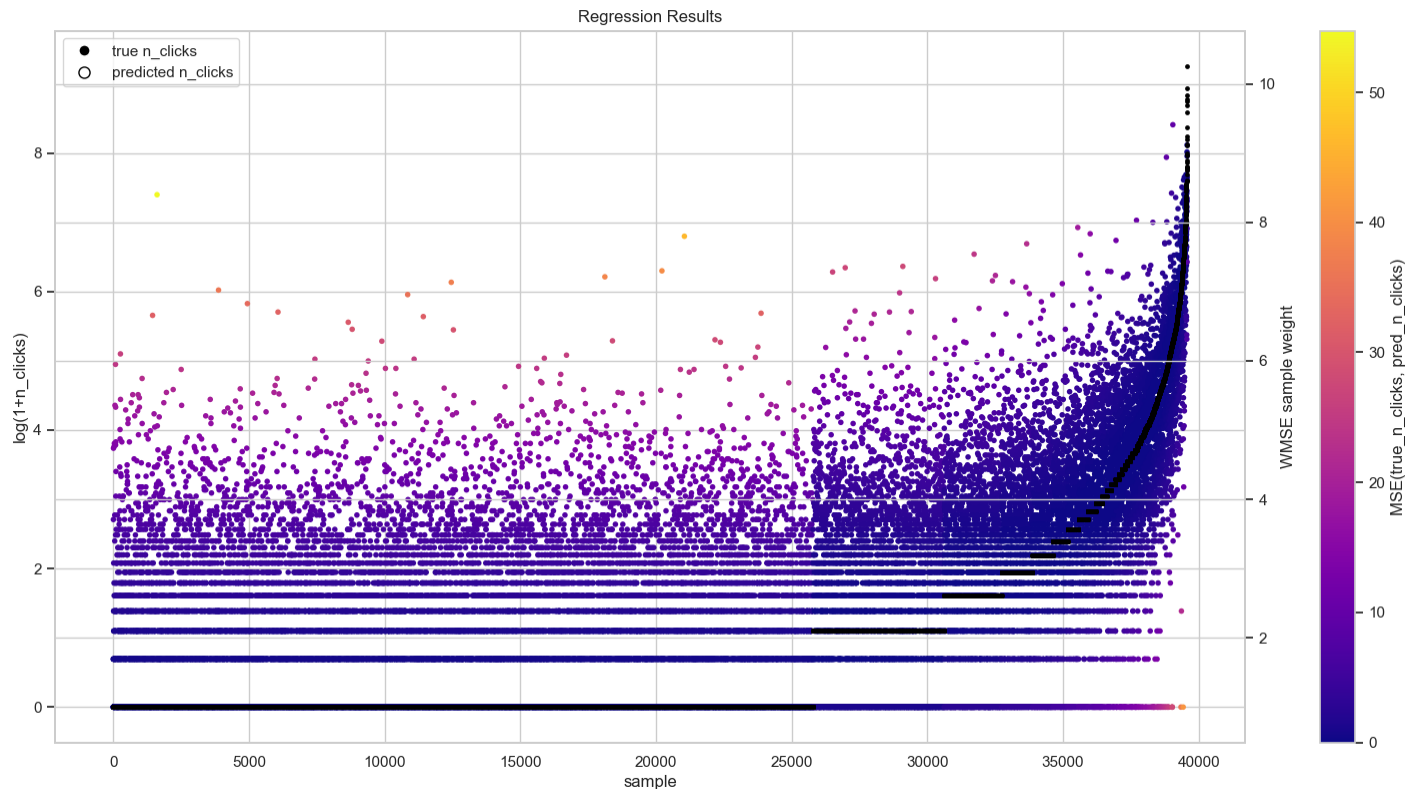


XGBoost + Weighted Oversampling, no log

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WMSE = 1.22

Without WO, WMSE = 1.26





XGBoost + WO, no log, stratified splitting

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WMSE = 0.91

