Job-SDF: A Multi-Granularity Dataset for Job Skill Demand Forecasting and Benchmarking

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Background

❖ Job Skill Demand Forecasting (Job-SDF)

➢ What is **Job Skill Demand?**

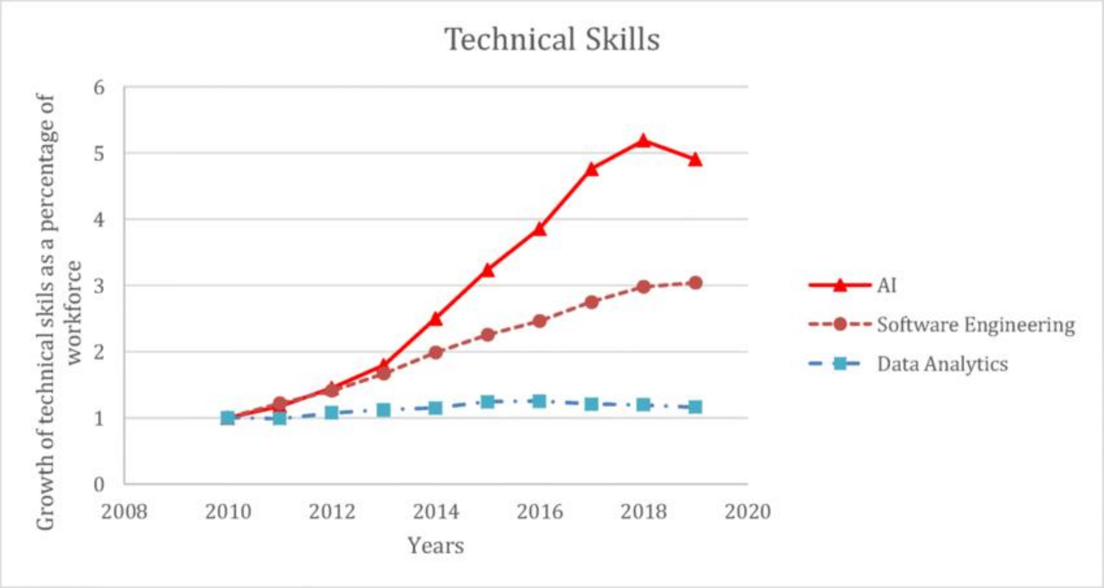


Figure 1. This figure contextualizes the growth in AI against growth in Software Engineering and Data Analysis.[1]

[1] Fedyk, Anastassia, et al. "Is artificial intelligence improving the audit process?." Review of Accounting Studies 27.3 (2022): 938-985.

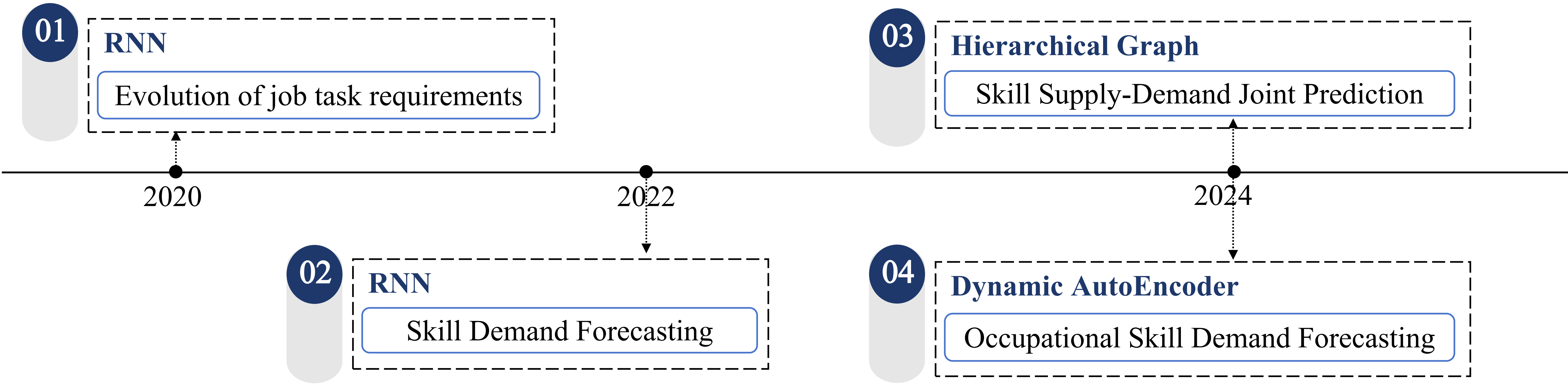
➢ What are the **benefits** of Job-SDF? (helpful for)

- addressing skill shortages and mismatches [2]
- promoting skill development [3]
- fostering continuous self-learning [4]

[2] James J Heckman, et al. The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. Journal of Labor economics, 24(3):411–482, 2006.
[3] Chuan Qin, er al. Automatic skill-oriented question generation and recommendation for intelligent job interviews. ACM Transactions on Information Systems, 42(1):1–32, 2023.
[4] Marios Kokkodis, et al. Demand-aware career path recommendations: A reinforcement learning approach. Management science, 67(7):4362–4383, 2021.

Related Works

❖ Job Skill Demand Forecasting

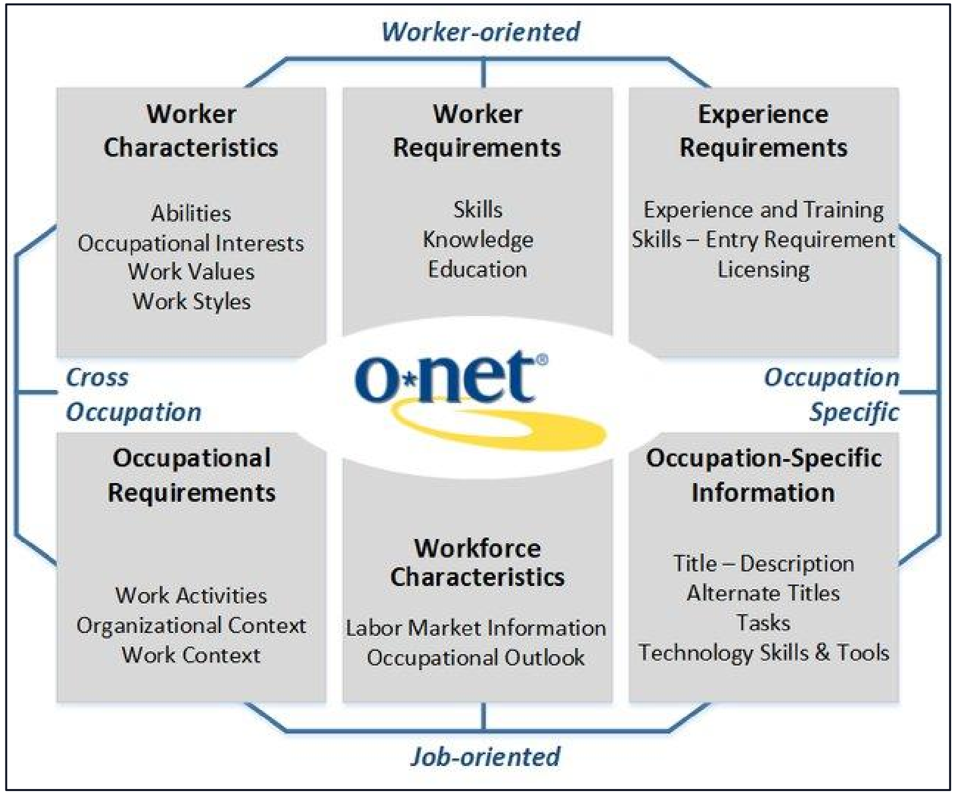


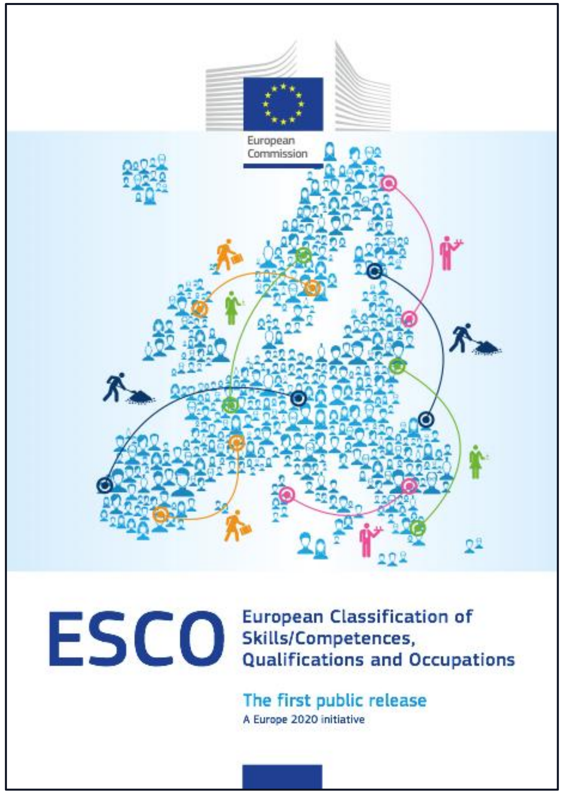
- ➢ A major challenge impeding progress in this field is the lack of comprehensive and publicly accessible datasets.
- ➢ Existing studies do not provide open-source datasets, making it difficult for researchers to replicate experimental results and identify bottlenecks in current research.
- ➢ Furthermore, these datasets primarily focus on predicting skill demand variations across different occupations, with a notable lack of modeling and prediction at other granularities, such as companies or regions.

Related Works

❖ Skill Related Datasets

➢ While open-source skill-related datasets such as O*NET and ESCO provide skill taxonomies, they do not quantify skill demand.





- **The absence of comprehensive datasets presents a significant challenge, impeding research and the advancement of this field.**

Dataset

❖ Job Skill Demand Dataset

➢ Data Collection and Processing

- Job Advertisement Collection: *Job Requirement, Company, Occupation, Region, Posting Time*
- Job Skill Extraction: explicitly extract skill requirements from the *Job Requirement* (*NER model)*
- Job Skill Demand Estimation**:** calculate skill demand at various granularities

$$D_{s,t,\bar{a}}^{i,j,\ldots,k} = \sum_{p \in \mathcal{P}_t} \mathbf{1}(s \in p) \cdot \mathbf{1}\left(a^i \in p \wedge a^j \in p \wedge \ldots \wedge a^k \in p\right)$$

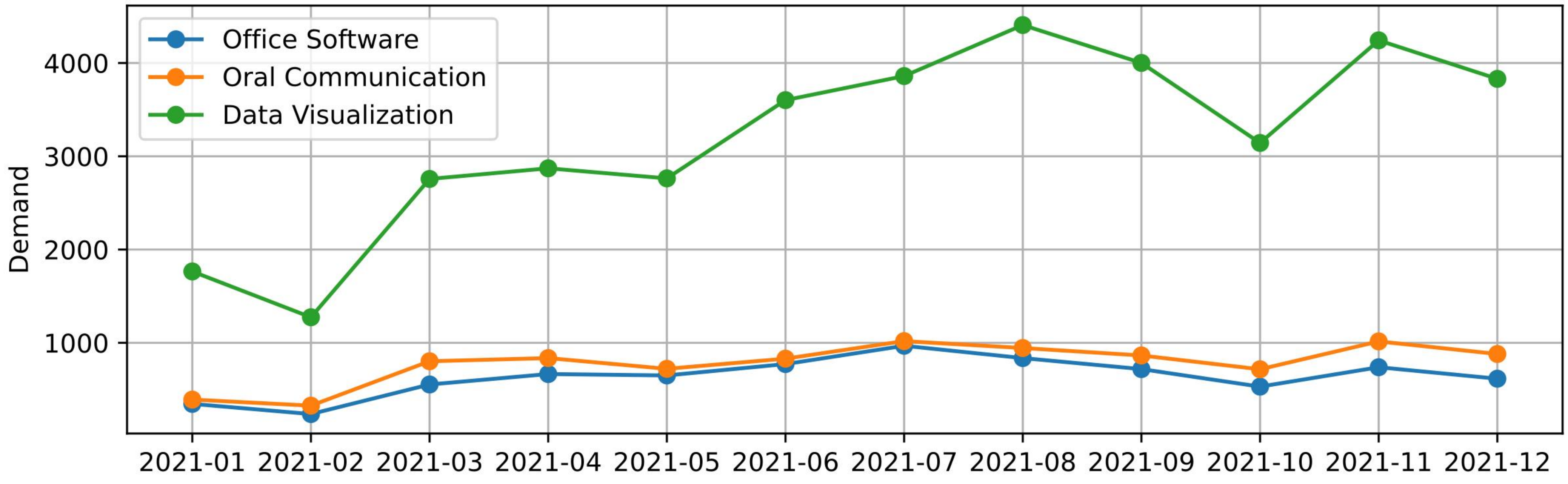
➢ Job Skill Demand Forecasting Task

- Given a granularity or a set of granularities g and the observed job skill demand series from the previous *K* timestamps, the goal of job skill demand forecasting is to learn a forecasting model *M* to predict the demand values for the next *H* timestamps.

Dataset

❖ Case

➢ Monthly Skill Demand



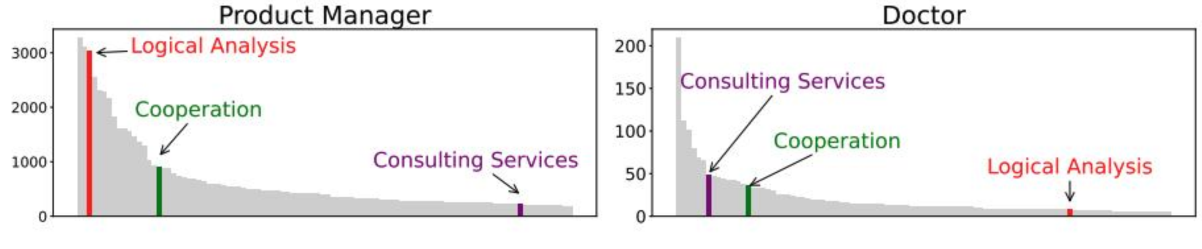
The monthly skill demand of office software, oral communication and data visualization in 2021.

Dataset

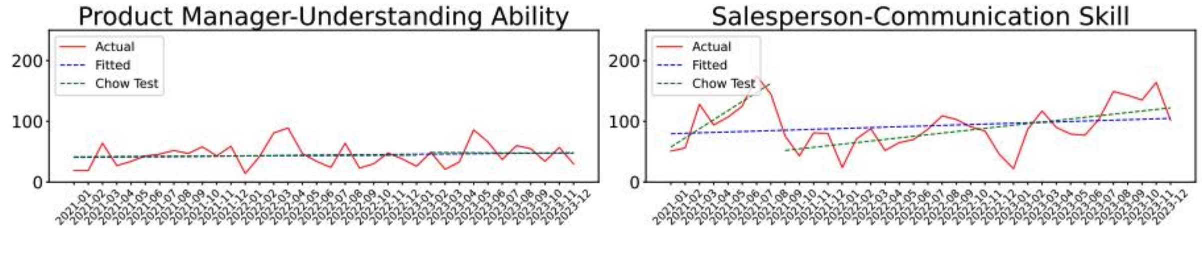
❖ Dataset Analysis

➢ <u>What are the data **characteristics** of Job-SDF?</u>

- <u>Varying Nature of Skill Demand</u>
- <u>Structural Break Phenomenon</u>
- <u>Inter-Series Correlation</u>



(a) The skill demands under two occupations.



(b) Appying the Chow test to two skill demand time series.

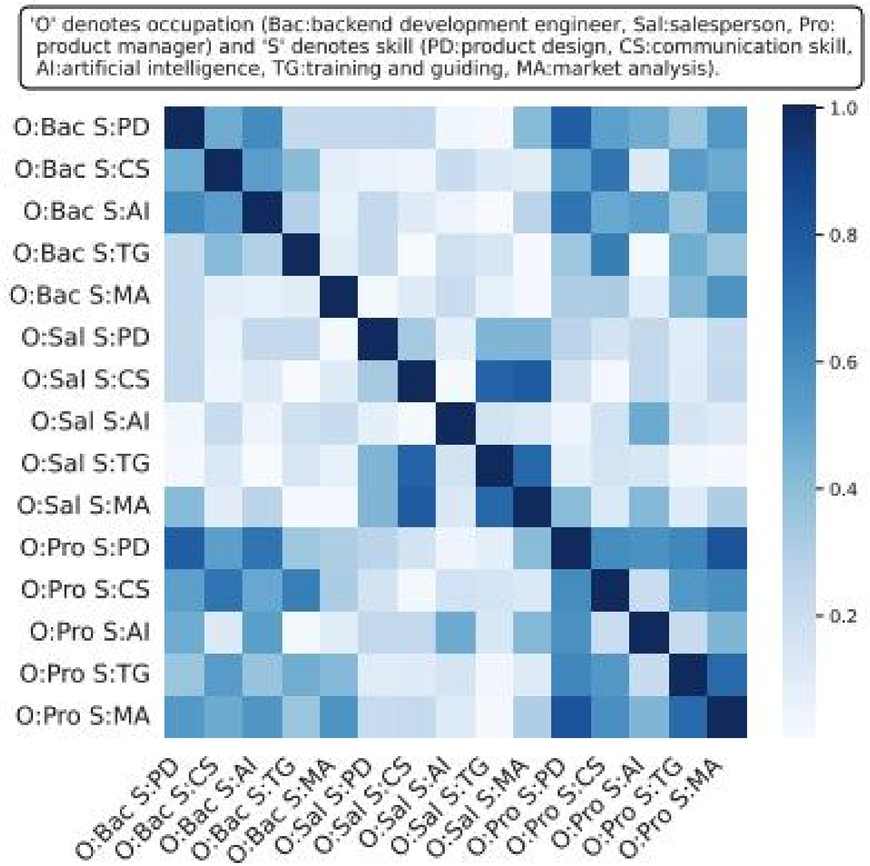


Figure 2: Pearson Correlation Coefficients.

Benchmark

❖ Benchmark Tasks

- ➢ Job-Skill Demand Forecasting
  - MAE, RMSE
- ➢ Low-Demand Skill Prediction
  - SMAPE, RRMSE
- ➢ Forecasting on Job-Skill Demand Series with Structural Breaks
  - Chow test to detect structural breaks

❖ Benchmark Models

- ➢ Statistical Time Series Model
- ➢ RNN-based Model
- ➢ Transformer-based Model
- ➢ MLP-based Model
- ➢ Graph-based Models
- ➢ Fourier-based Model

Benchmark

❖ Job Skill Demand forecasting performance comparisons

Table 1: Performance comparison on MAE and RMSE.

Model	L1-Occupation		L2-Occupation		Region&L1-O		Region&L2-O		Company	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
ARIMA	20.27	256.89	6.46	115.79	3.98	58.65	1.31	27.42	1.31	38.88
Prophet	29.15	356.67	8.95	161.01	5.08	72.21	1.62	33.02	1.55	41.19
LSTM	19.05	194.67	7.09	116.36	3.92	51.59	1.29	23.31	1.35	26.47
SegRNN	12.28	108.28	5.01	68.83	3.14	34.26	1.05	15.96	1.01	16.03
CHGH	22.09	261.49	7.09	116.58	3.91	51.46	1.28	23.24	1.34	26.52
Pre-DyGAE	22.98	187.90	7.04	82.97	4.24	38.62	1.37	17.39	1.24	18.24
Transformer	22.06	215.09	7.58	118.21	4.01	52.04	1.35	23.44	1.26	24.99
Autoformer	23.06	186.76	8.22	100.02	6.45	57.77	2.41	24.10	3.31	38.55
Informer	22.21	205.24	7.43	117.38	3.88	50.13	1.30	23.07	1.26	24.92
Reformer	22.11	204.35	7.46	116.60	3.91	50.95	1.25	22.81	1.54	27.37
FEDformer	22.87	181.93	7.46	88.97	4.63	43.21	1.98	21.73	2.43	26.92
NStransformer	17.36	149.46	5.75	86.24	3.45	37.09	1.15	17.45	2.13	34.83
PatchTST	14.91	141.06	5.15	78.86	3.10	35.38	1.04	16.57	1.01	19.09
DLinear	16.61	154.88	5.44	81.61	3.24	36.67	1.07	16.79	1.05	18.85
TSMixer	21.34	192.85	8.14	106.65	5.81	62.14	5.95	68.26	13.96	144.96
FreTS	16.47	167.61	6.52	106.39	3.65	47.81	1.22	21.92	1.26	25.39
FiLM	12.95	117.17	5.08	65.65	3.24	29.90	1.14	14.01	1.17	15.87
Koopa	19.91	179.30	6.05	91.87	3.53	40.73	1.15	18.71	1.08	20.18

Benchmark

❖ Job Skill Demand forecasting performance comparisons

Table 2: Performance comparison on SMAPE and RRMSE.

Model	L1-Occupation (%)		L2-Occupation (%)		Region&L1-O (%)		Region&L2-O (%)		Company (%)	
	SMAPE	RRMSE	SMAPE	RRMSE	SMAPE	RRMSE	SMAPE	RRMSE	SMAPE	RRMSE
ARIMA	35.72	47.89	25.00	58.87	23.86	58.07	13.58	73.57	20.17	147.94
Prophet	41.22	67.78	28.35	88.47	26.75	71.60	15.07	93.04	22.31	167.77
LSTM	41.38	57.90	32.85	83.70	31.58	68.40	22.93	87.36	30.26	174.40
SegRNN	39.81	37.58	33.35	50.53	35.30	48.53	23.84	61.90	33.07	86.27
CHGH	40.27	66.05	29.60	84.10	28.11	68.42	17.42	87.45	26.72	176.70
PreDyGAE	49.87	83.67	60.54	83.60	59.32	66.56	72.67	98.09	26.21	145.73
Transformer	55.59	64.25	44.23	84.27	31.15	76.16	33.04	86.87	27.61	164.36
Autoformer	70.28	53.75	74.37	63.40	90.14	65.57	91.51	74.46	107.05	99.60
Informer	56.85	58.18	44.04	88.72	34.75	69.59	29.29	90.15	32.41	164.37
Reformer	56.58	61.35	40.58	83.70	32.21	72.87	20.86	90.85	45.25	169.87
FEDformer	69.30	54.03	69.29	60.00	73.17	52.69	81.73	70.06	94.19	97.97
NStransformer	38.11	47.19	26.30	60.73	24.98	48.89	14.55	63.29	24.20	100.78
PatchTST	34.70	51.17	24.52	58.80	25.15	44.96	13.50	67.48	19.89	115.34
DLinear	41.84	52.89	34.35	60.22	33.47	51.05	25.77	64.65	30.71	108.66
TSMixer	56.59	61.17	72.29	99.35	82.48	87.29	120.85	96.49	155.20	102.14
FreTS	39.76	54.42	30.18	80.44	28.58	66.11	17.62	85.04	27.24	174.56
FiLM	39.51	37.55	29.65	43.86	28.79	37.66	17.24	47.75	25.72	76.92
Koopa	37.84	58.30	25.72	65.34	24.41	57.81	13.98	74.00	20.43	123.96

Benchmark

❖ Performance comparisons on data with structural breaks

Table 3: Performance comparison on data with structural breaks on MAE and RMSE.

Model	L1-Occupation		L2-Occupation		Region&L1-O		Region&L2-O		Company	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
LSTM	87.30	554.46	57.95	400.22	18.99	149.53	7.91	52.38	24.40	159.02
SegRNN	61.92	390.54	43.97	276.57	15.85	114.04	6.56	37.84	17.98	112.13
CHGH	94.30	629.32	58.06	401.45	19.00	149.75	7.90	52.50	24.37	159.44
PreGyGAE	78.35	493.83	48.69	336.15	17.49	136.66	7.31	38.88	19.76	164.43
Transformer	98.66	580.58	61.73	404.17	19.37	151.12	8.45	55.46	22.41	152.27
Autoformer	107.22	533.06	67.66	350.97	26.84	156.50	12.19	63.04	44.10	208.96
Informer	98.89	570.35	59.95	402.75	19.03	146.91	7.72	49.15	22.37	151.87
Reformer	98.14	569.83	60.71	401.21	19.25	149.91	7.52	49.10	25.65	160.69
FEDformer	105.43	532.24	62.10	325.10	20.49	128.45	10.37	55.47	34.09	155.28
NStransformer	82.43	462.24	49.30	318.44	16.59	119.91	6.85	37.56	40.05	196.03
PatchTST	77.44	474.86	45.02	303.76	14.88	111.01	6.56	38.60	18.03	127.72
DLinear	81.17	485.25	46.67	307.34	15.94	118.94	6.50	37.72	18.18	124.32
TSMixer	107.47	614.93	83.60	479.39	29.99	187.08	25.83	190.29	155.10	766.58
FreTS	82.45	537.12	56.54	393.38	18.55	148.33	7.88	52.87	24.21	160.01
FiLM	62.86	404.82	42.63	260.99	14.31	101.23	6.37	32.28	18.78	110.65
Koopa	91.26	516.75	50.44	324.15	17.43	128.39	7.07	41.29	19.04	133.26

Benchmark

❖ Performance comparisons on data with structural breaks

Table 4: Performance comparison on data with structural breaks on RRMSE and SMAPE.

Model	L1-Occupation (%)		L2-Occupation (%)		Region&L1-O (%)		Region&L2-O (%)		Company (%)	
	SMAPE	RRMSE	SMAPE	RRMSE	SMAPE	RRMSE	SMAPE	RRMSE	SMAPE	RRMSE
LSTM	43.78	58.05	48.93	84.46	46.64	78.31	42.03	58.48	68.38	187.30
SegRNN	39.22	37.80	43.09	51.14	45.17	54.31	39.41	41.40	57.45	89.65
CHGH	44.91	66.31	48.90	84.87	45.43	78.32	39.79	58.89	68.36	189.91
PreDyGAE	52.35	47.15	56.56	59.31	52.06	61.22	44.13	42.31	70.26	106.88
Transformer	50.01	64.47	53.10	84.95	46.50	86.56	47.67	61.23	64.92	177.43
Autoformer	63.46	54.08	68.62	64.14	87.93	68.97	88.95	63.85	115.00	100.60
Informer	51.11	58.40	51.89	89.70	47.81	80.86	44.90	57.55	65.11	177.16
Reformer	50.79	61.59	51.51	84.53	46.86	84.15	40.81	58.59	72.36	181.36
FEDformer	62.83	54.37	64.37	60.84	72.24	58.55	80.03	54.29	103.27	100.65
NStransformer	45.36	47.46	47.63	61.85	43.04	57.60	36.72	39.72	170.57	113.87
PatchTST	40.89	51.48	43.26	59.69	41.51	51.85	34.74	43.12	55.26	122.56
DLinear	43.14	53.20	45.25	61.13	45.26	58.80	41.15	41.71	57.65	115.24
TSMixer	54.31	61.31	76.08	99.84	85.12	95.81	117.39	93.66	160.55	102.23
FreTS	42.44	54.59	48.24	81.17	45.39	75.43	39.85	57.83	68.39	187.94
FiLM	38.96	37.82	44.23	44.52	44.95	43.06	40.05	30.80	56.37	80.77
Koopa	46.45	58.59	47.13	66.28	42.60	66.20	36.24	47.48	58.98	131.77

Conclusion

❖ Job-SDF

- ➢ Job-SDF, designed for training and benchmarking job-skill demand forecasting models.
- ➢ Extensive experiments to compare the performance of various methods in predicting skill demand at different granularities.

Source Code

Author Email