

BTS: Building Time-Series Dataset: Empowering Large-Scale Building Analytics

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A NeurIPS Dataset and Benchmark 2024 poster.

Official repo: https://github.com/cruiseresearchgroup/DIEF_BTS/

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BTS

Building Time-Series Dataset

- 3 Buildings



Anonymized buildings in Australia.
Pictures for illustrative purposes only.
Photo by [Simone Hutsch](#) on [Unsplash](#)

BTS

Building Time-Series

Dataset

- 3 Buildings
- 3 Years



2021

3 Years

2024

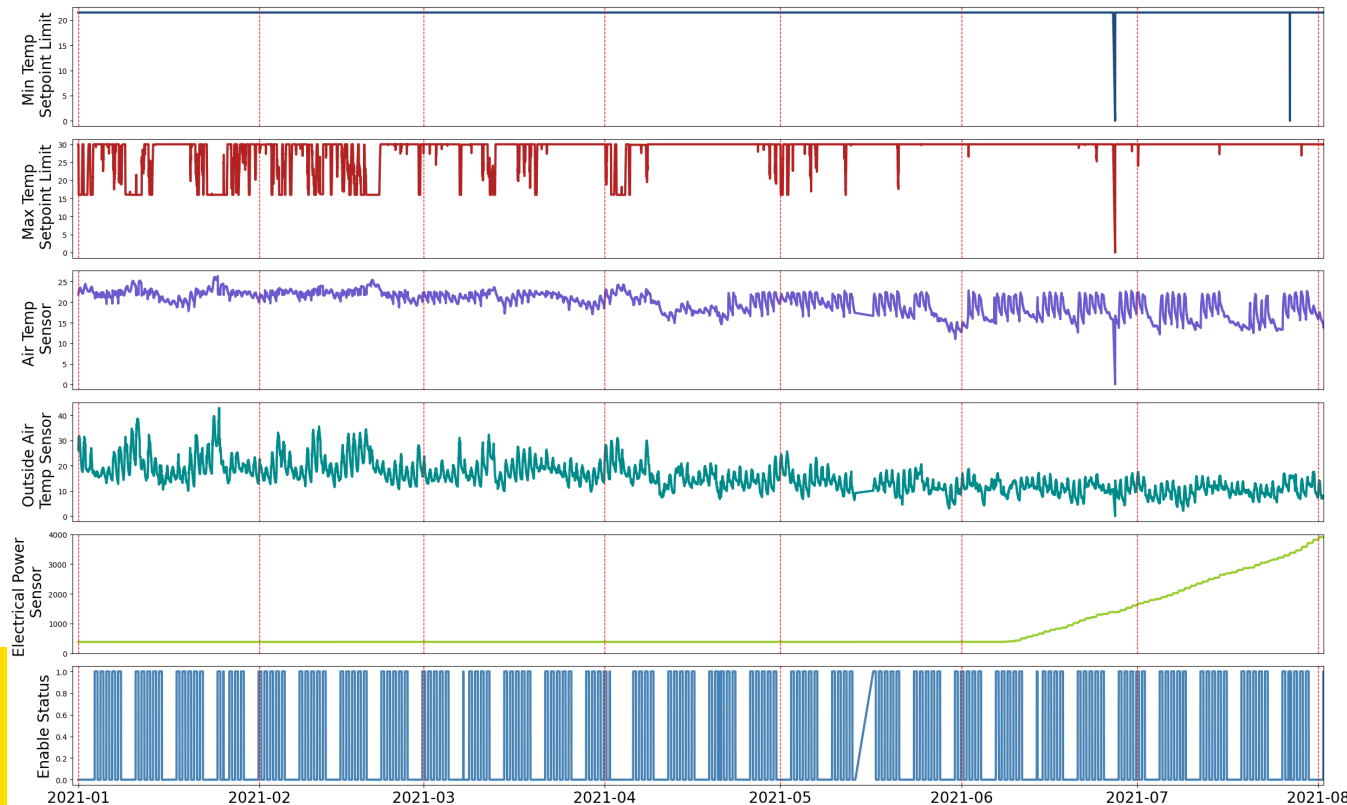
BTS

Building Time-Series Dataset

- 3 Buildings
- 3 Years
- >15 000 Time-series
- >300 Classes



Visualisation of six timeseries from the snippet



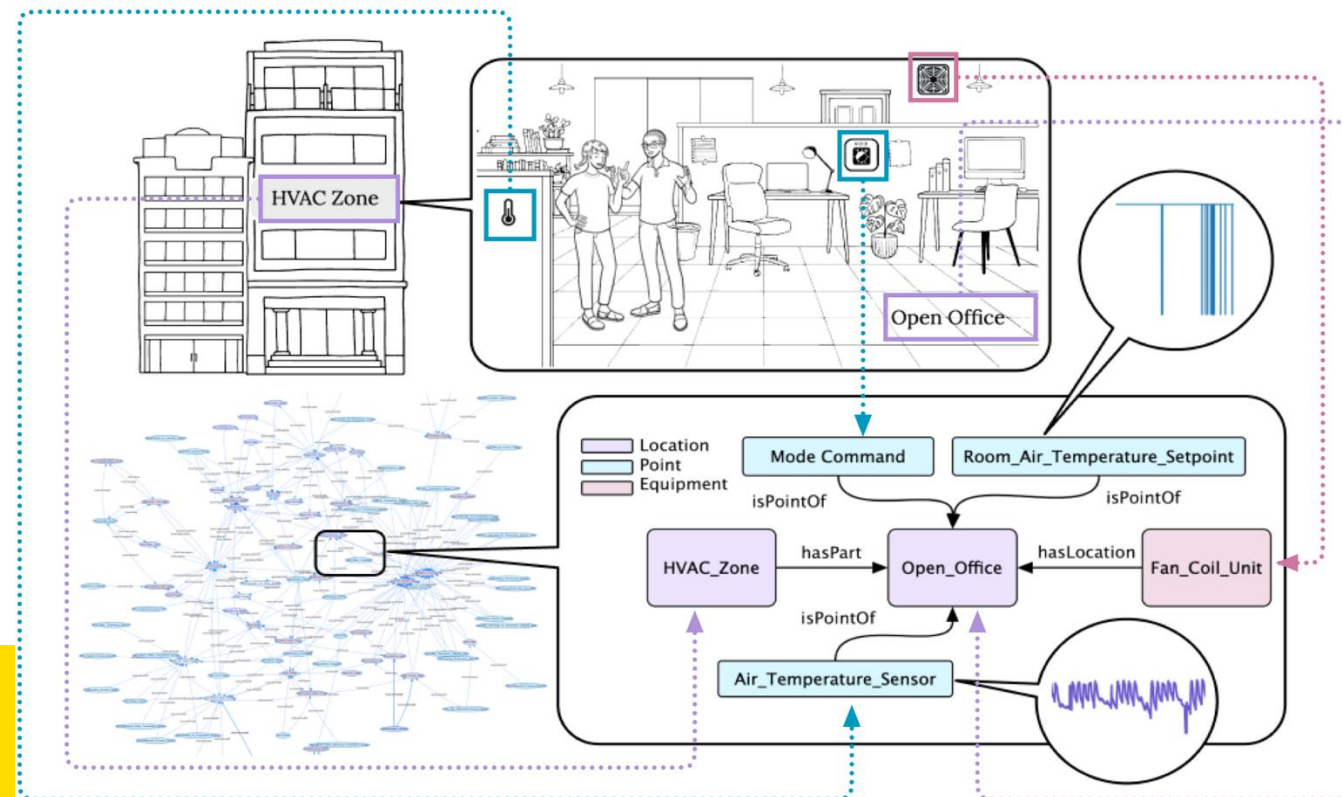
BTS

Building Time-Series Dataset

- 3 Buildings
- 3 Years
- >15 000 Time-series
- >300 Classes
- Knowledge Graph

The knowledge graph describes the “**physical, logical and virtual assets** in buildings and the **relationships** between them.”

We use the Brick schema: 



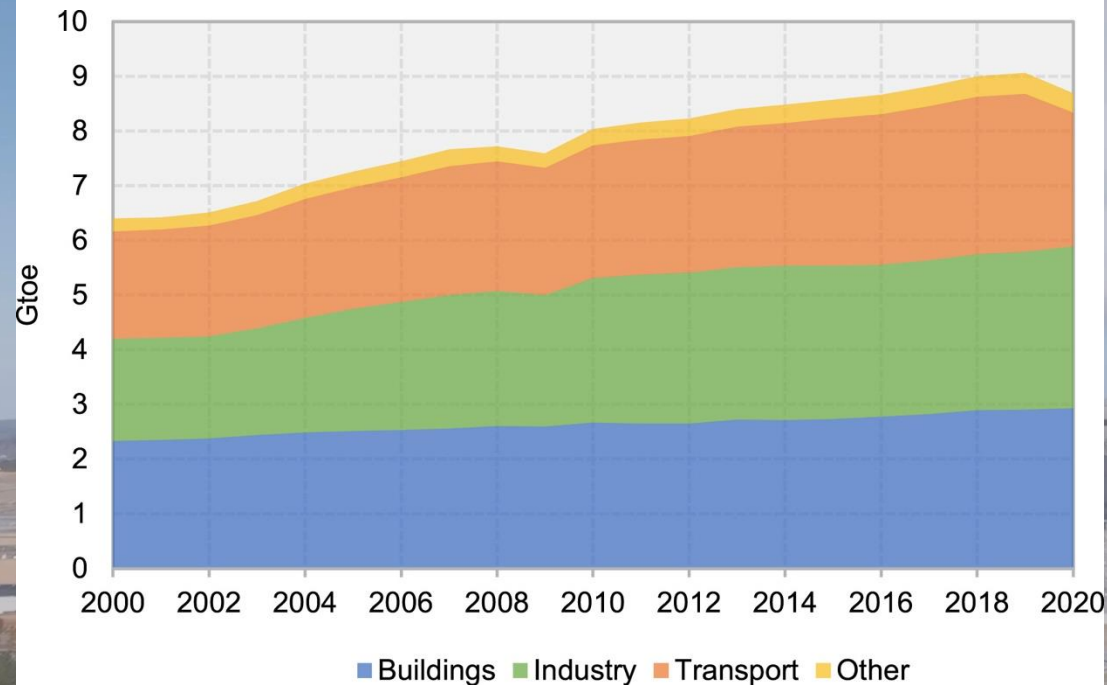
Why Building Analytics?



Why Building Analytics?

A **third** of global energy consumption.

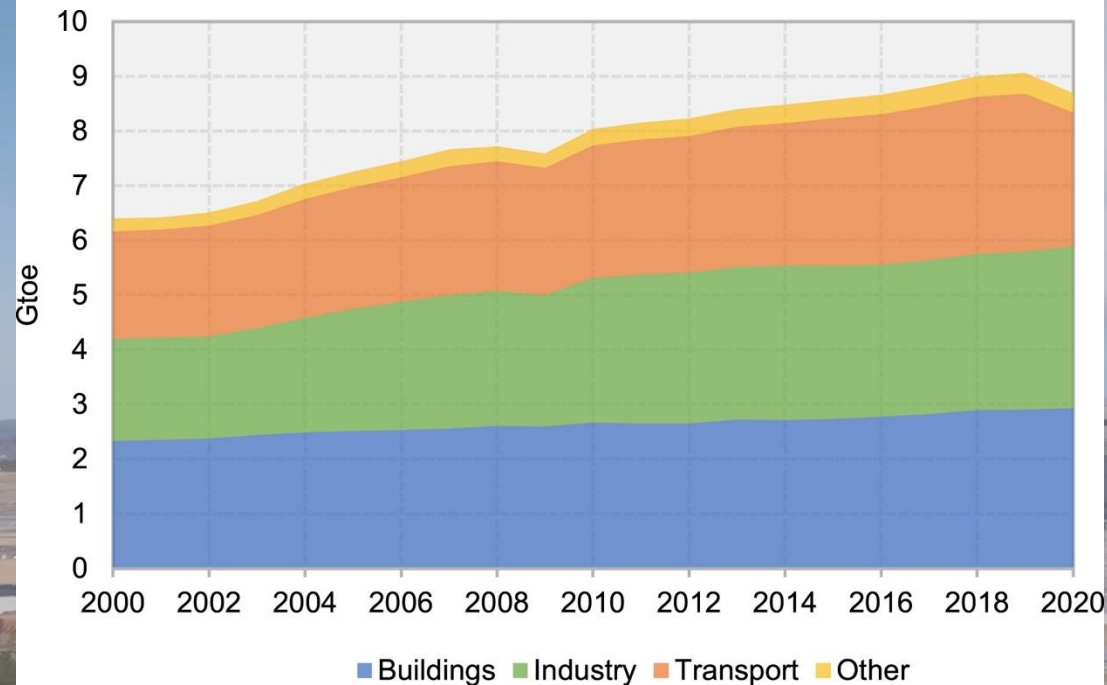
(Gtoe: Giga tonnes of oil equivalent)



Why Building Analytics?

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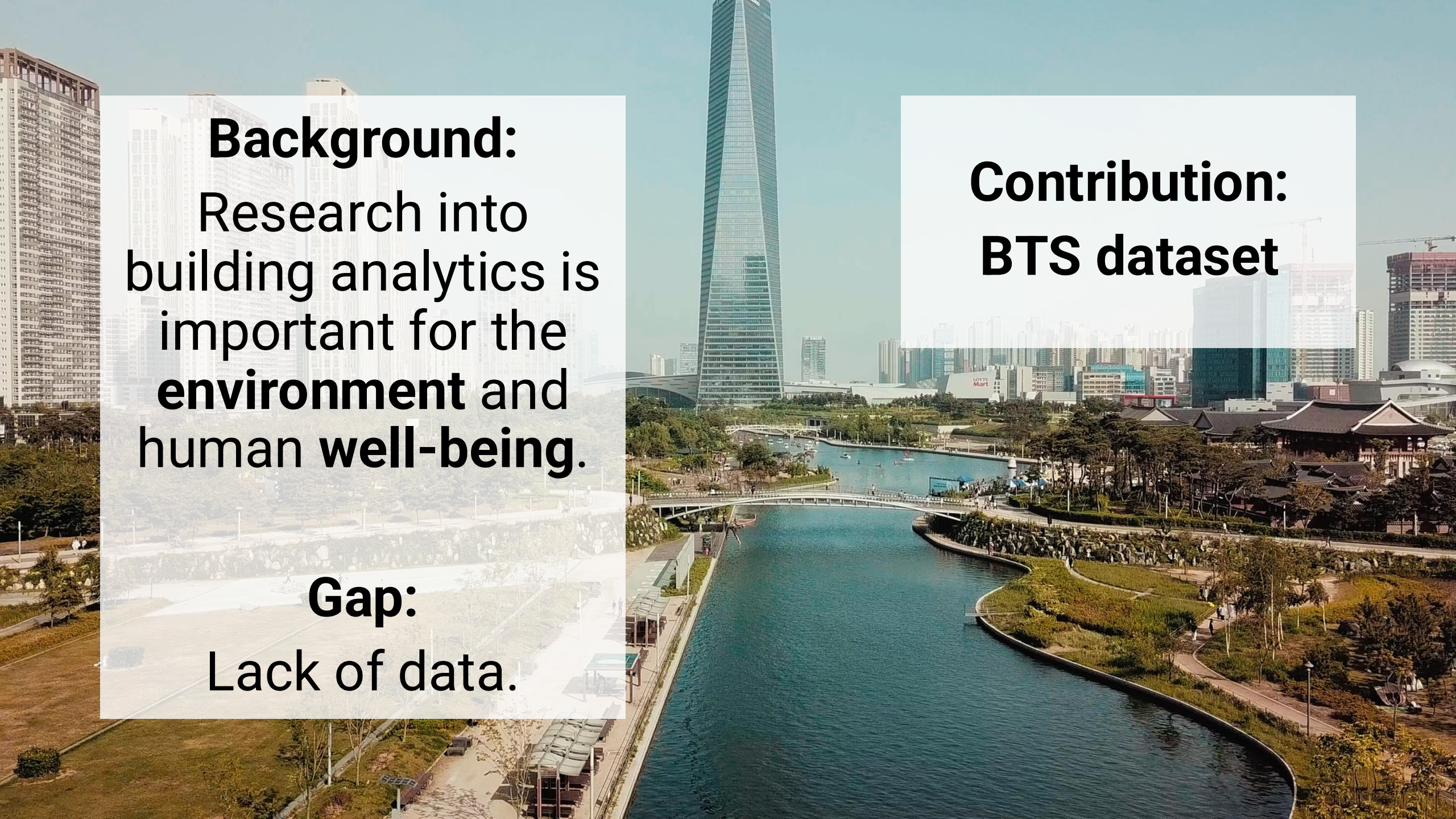
A **quarter** of CO₂ emissions.

Table 1. Share of direct and indirect CO₂ emissions by sector in 2019.

| Sector | Direct | Indirect | Total |
|-----------|--------|----------|-------|
| Industry | 19% | 19% | 38% |
| Buildings | 9% | 19% | 28% |
| Transport | 25% | 3% | 28% |
| Other | 2% | 4% | 6% |

Why Building Analytics?

As we spend more time in buildings, they will have increasing influence over our physical and mental wellbeing.

An aerial photograph of a modern city. In the center, a tall, slender skyscraper with a glass facade rises above the skyline. Below it, a river flows through a park area with green lawns, trees, and a pedestrian bridge. In the background, other high-rise buildings and a traditional Korean-style pavilion are visible. The sky is clear and blue.

Background:
Research into building analytics is important for the **environment** and **human well-being**.

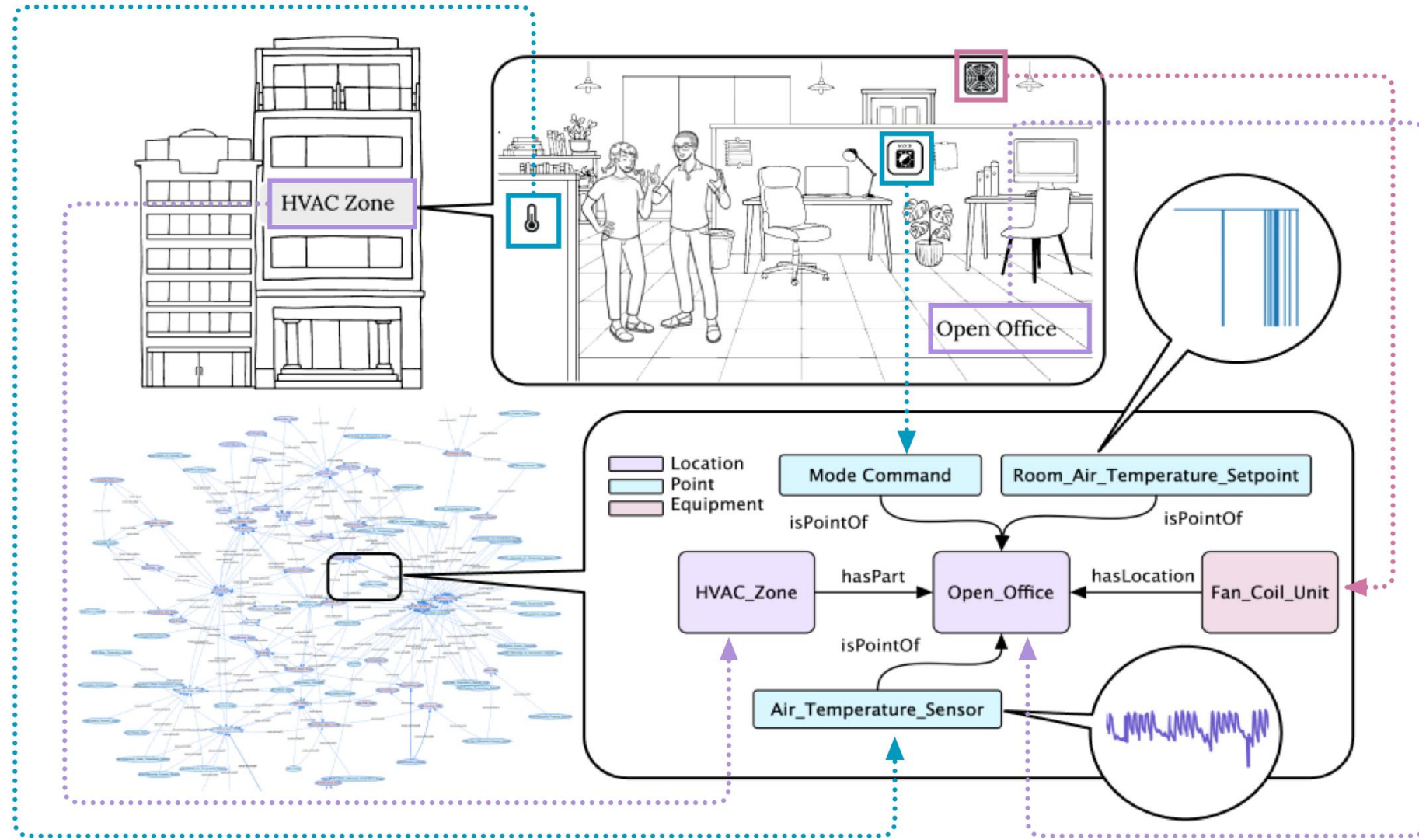
Gap:
Lack of data.

Contribution:
BTS dataset

BTS has 2 main components:

1. Multivariate timeseries from real-world building operations

2. Building meta-data in the form of a knowledge graph

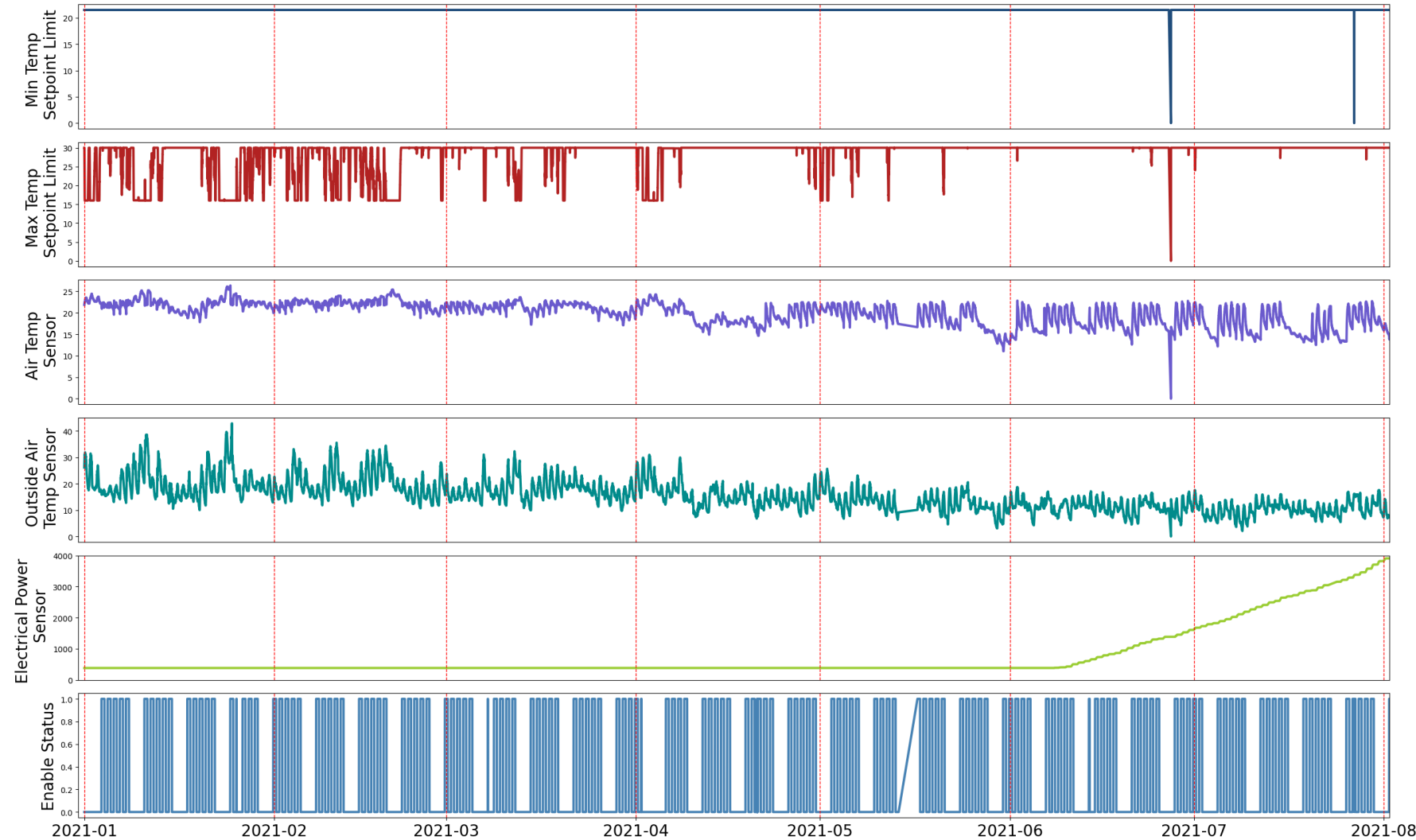


Timeseries: Diverse class and distribution

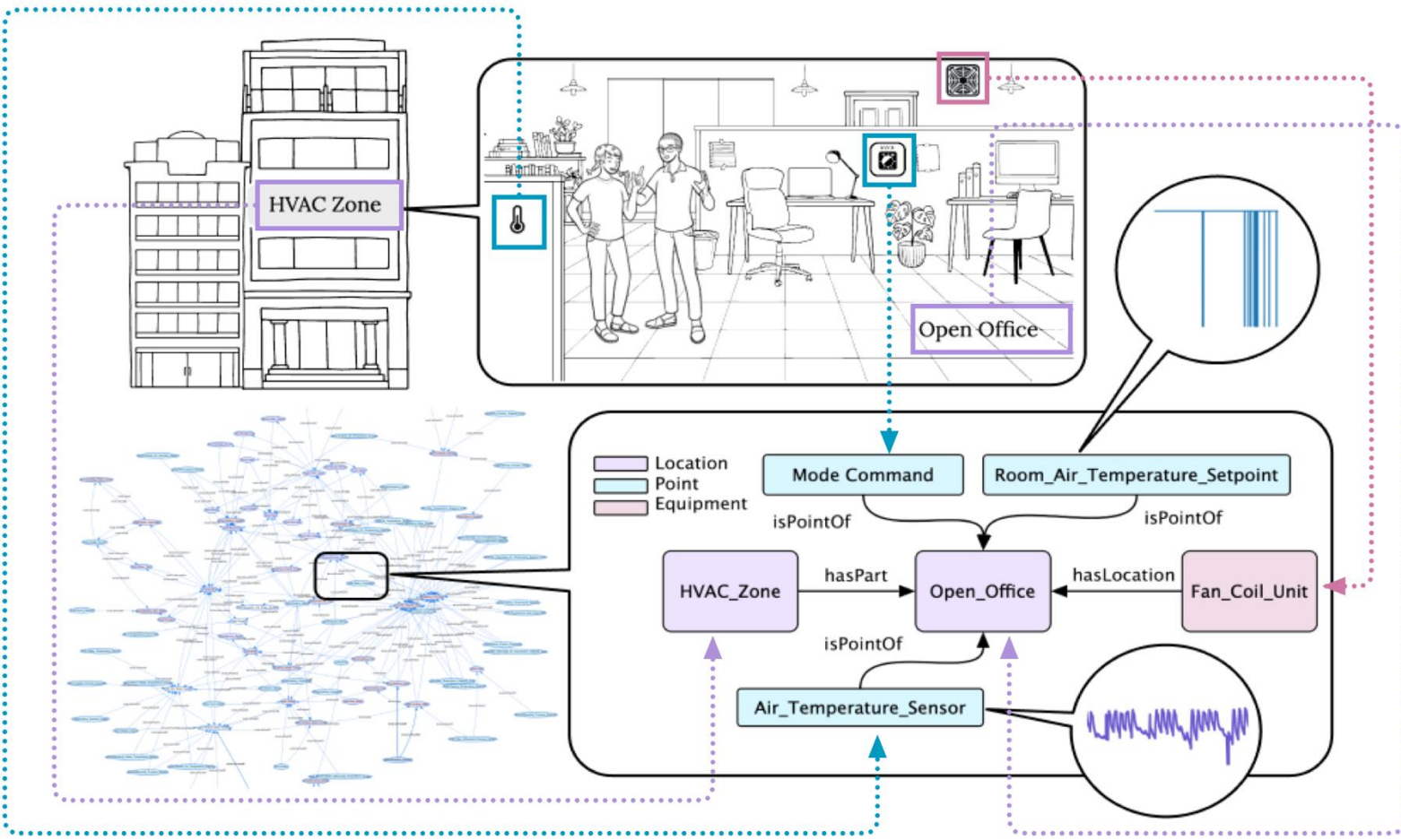
Most other timeseries dataset only have a single class with similar distributions family e.g., traffic, stock market, EEG, IMU.

BTS has few hundreds unique classes.

Visualisation of six timeseries from the snippet



Metadata Knowledge Graph using a standardized schema



- brick Entity
 - + brick Collection
 - + brick Equipment
 - + brick Location (deprecated)
 - + brick Measurable
 - brick Point
 - + brick Alarm
 - + brick Command
 - + brick Parameter
 - brick Sensor
 - + brick Adjust_Sensor
 - + brick Air_Grains_Sensor
 - brick Air_Quality_Sensor
 - brick Ammonia_Sensor
 - brick CO_Sensor

3 new Buildings, enabling: inter-building generalisation

- Transfer learning
- Domain adaptation
- Distribution shifts
- Few & Zero shots

| Count (Unique) | | LBNL59 | | BTS_A | | BTS_B | | BTS_C | |
|------------------|------------|---------------|------|------------------------------------|------------|------------|------|-------|-------|
| Top Level | Collection | 0 | (0) | 4 | (2) | 2 | (2) | 8 | (1) |
| | Equipment | 59 | (3) | 547 | (24) | 159 | (25) | 963 | (41) |
| | Location | 73 | (3) | 481 | (9) | 68 | (17) | 381 | (26) |
| | Point | 230 | (11) | 8374 | (126) | 851 | (57) | 10440 | (159) |
| Timeseries | | 337 | | 8349 | | 851 | | 5347 | |
| Point Subclass | Alarm | 0 | (0) | 798 | (16) | 5 | (2) | 109 | (8) |
| | Command | 0 | (0) | 363 | (6) | 97 | (5) | 785 | (13) |
| | Parameter | 0 | (0) | 79 | (6) | 36 | (2) | 935 | (17) |
| | Sensor | 144 | (8) | 4396 | (56) | 266 | (25) | 4062 | (68) |
| | Setpoint | 86 | (3) | 772 | (26) | 232 | (16) | 1629 | (41) |
| | Status | 0 | (0) | 1628 | (17) | 110 | (6) | 2187 | (19) |
| Location | | Berkeley, USA | | Undisclosed locations in Australia | | | | | |
| Start Date | | 01-01-2018 | | 01-01-2021 | 01-01-2021 | 23-06-2021 | | | |
| End Date | | 31-12-2020 | | 31-12-2023 | 31-12-2023 | 18-01-2024 | | | |
| Duration (Days) | | 1094 | | 1094 | 1094 | 939 | | | |
| Size Zipped (GB) | | 0.26 | | 8.48 | 1.31 | 8.98 | | | |

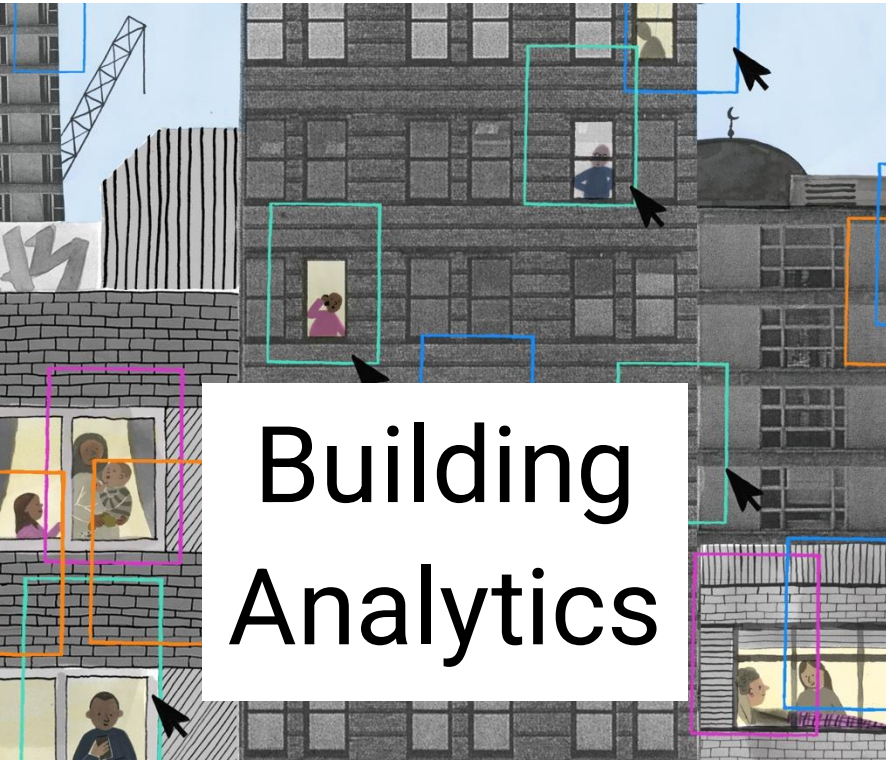
Why use BTS?

1

2

3

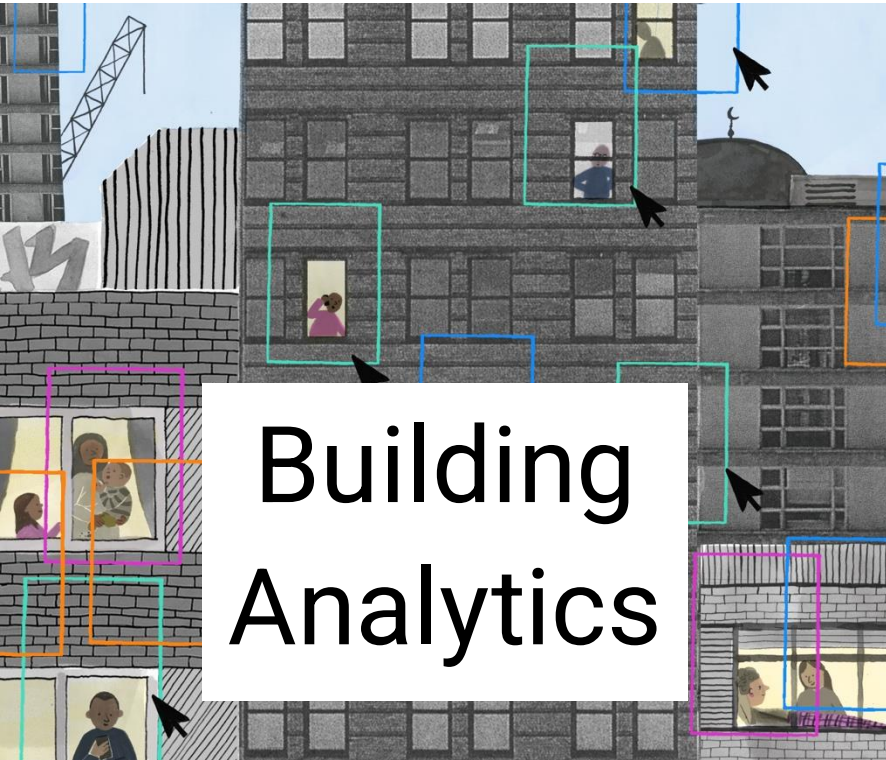
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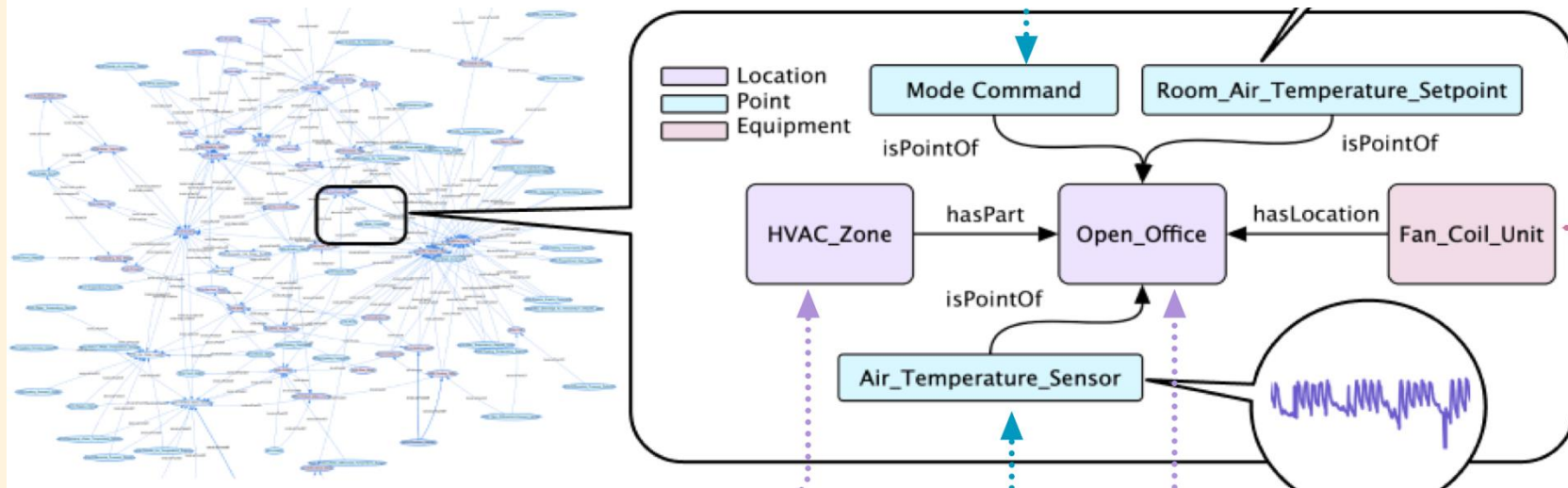
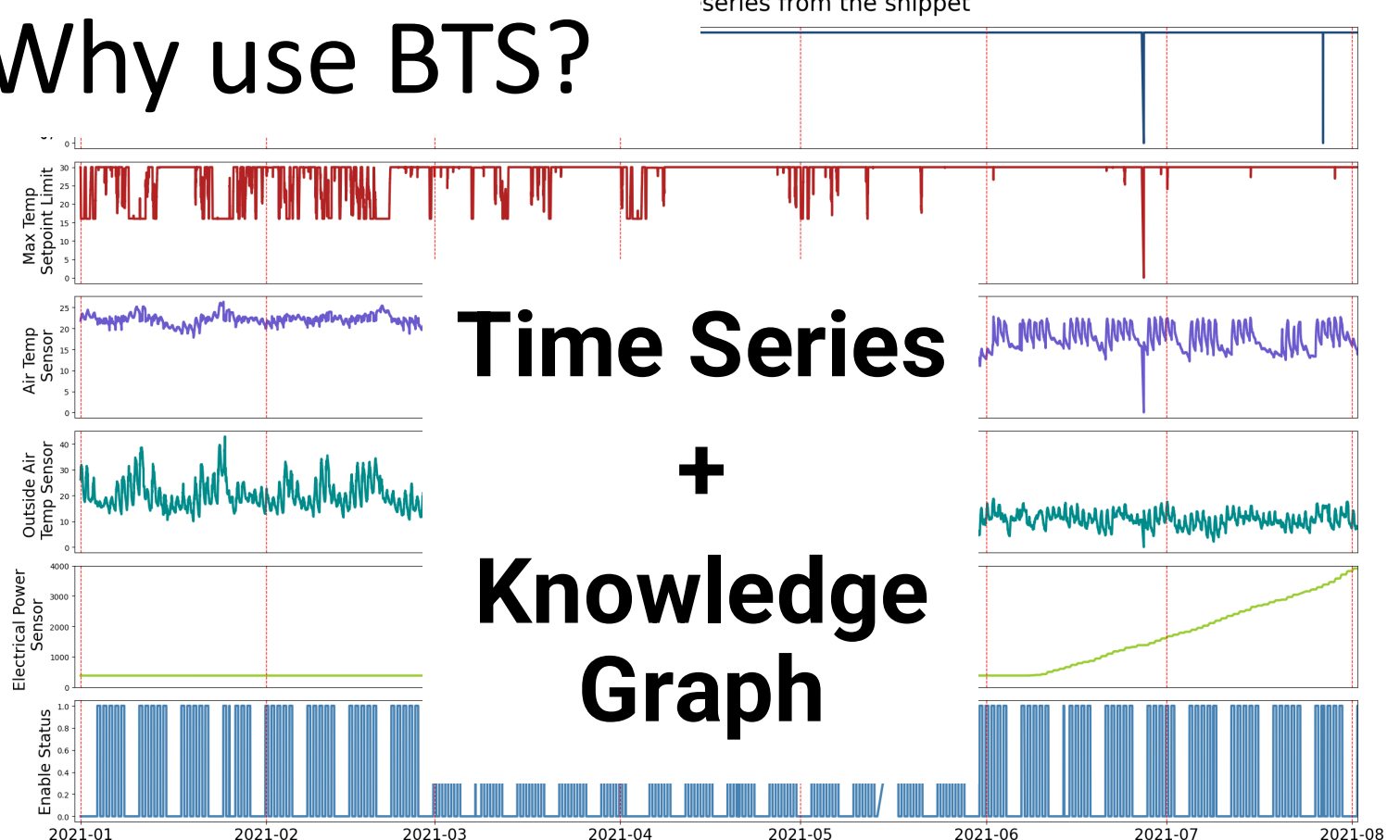
Example tasks:

- Forecasting
- Anomaly Detection
- **AI Chat for buildings:** To enables building managers to get data-driven insights via seamless interface like AI chat.





Why use BTS?



Why use BTS?

- **Unbalanced, Long-tailed**
 - Class: Some sensors (e.g., temperature sensor), are very common, while other sensors (e.g., dewpoint sensors) are very rare.
 - Data: The value for Alarm is zero most of the time.
- **Distribution shifts between buildings**
 - Few-shots, zero-shots, transfer learning, domain adaptation.
- **Irregular**
 - time step
 - any-variates

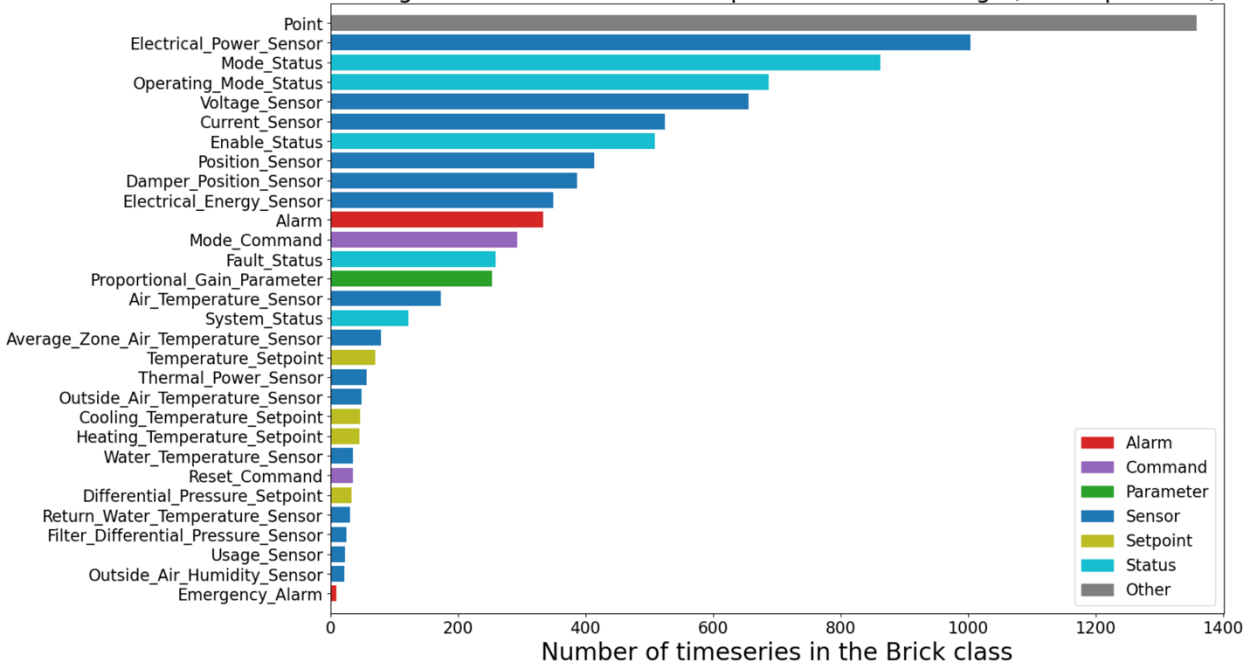


**Complexities
of
real-world
data
in the wild**

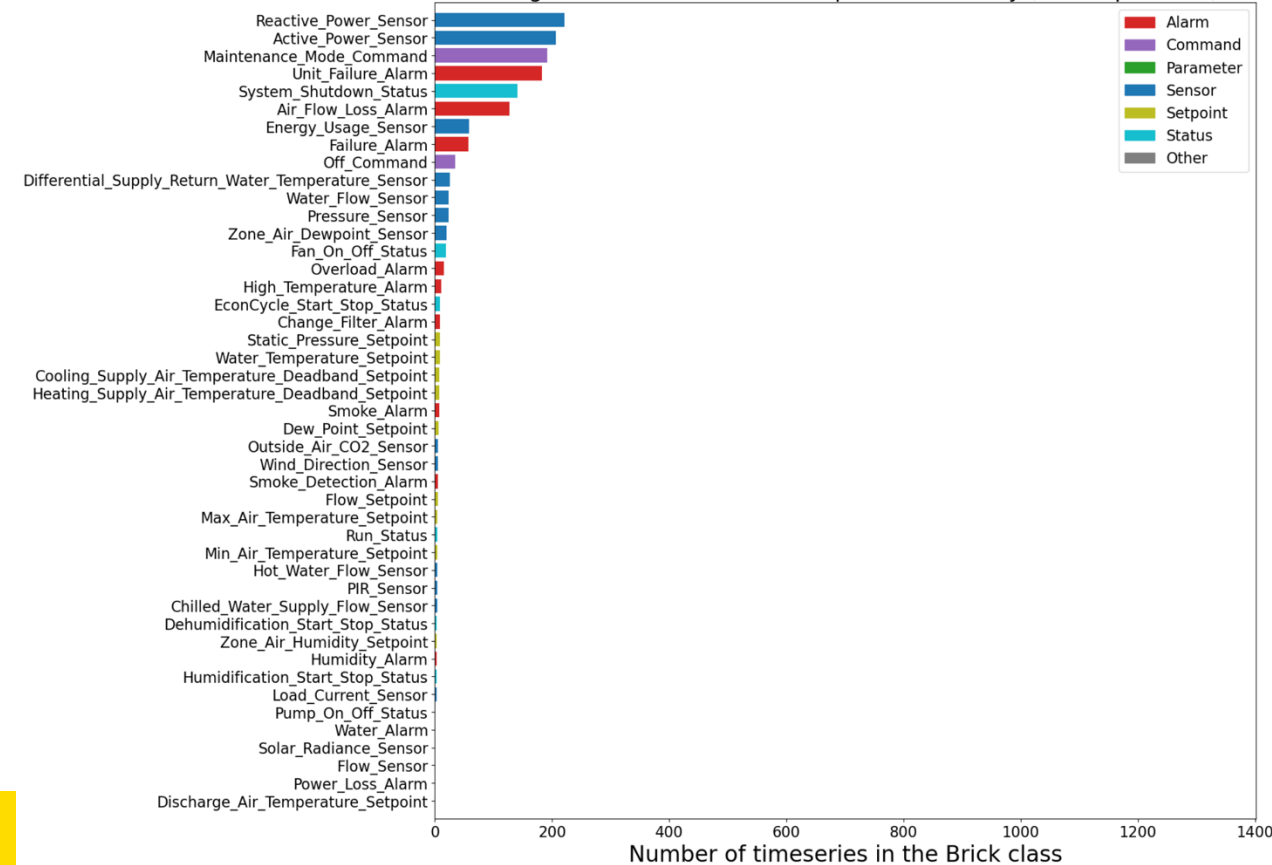
Electric_Power_Sensor have many instances.

But 45 unique classes only exist in Building A

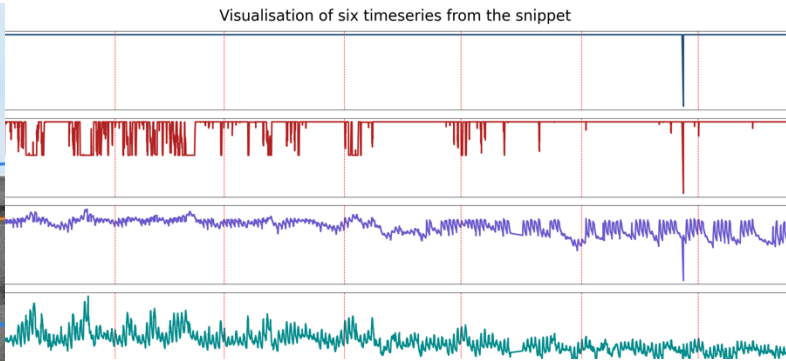
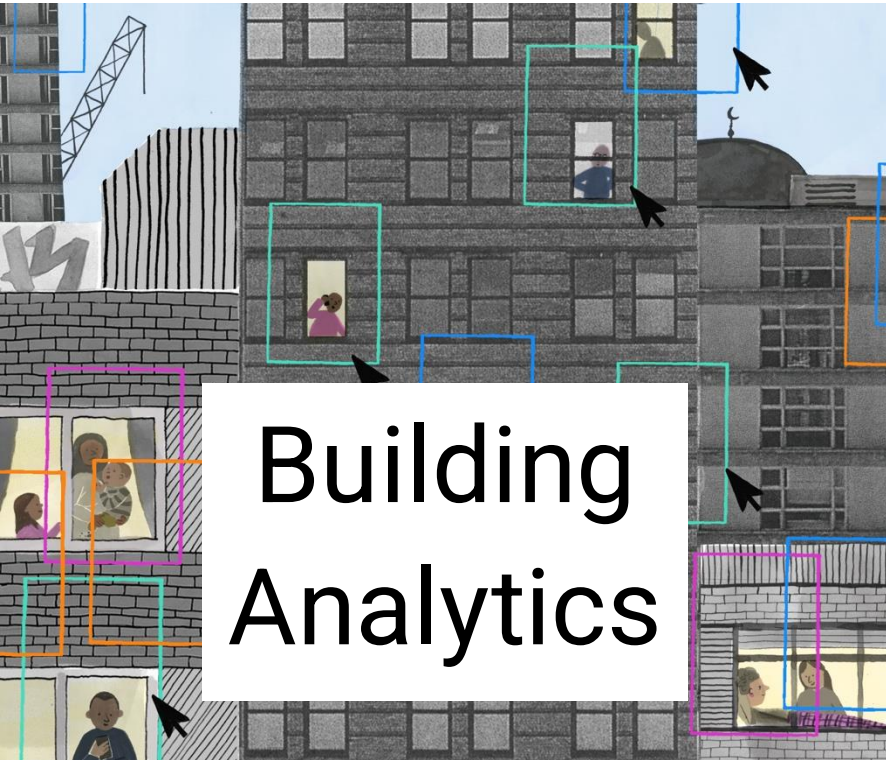
Histogram of class of timeseries present in all buildings (30 unique class)



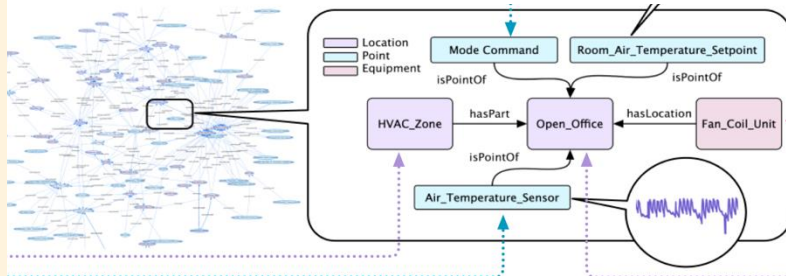
Histogram of class of timeseries present in A only (45 unique class)



Why use BTS?



Time Series + Knowledge Graph



**Complexities
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data
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Two Benchmarks

Multi-label timeseries classification

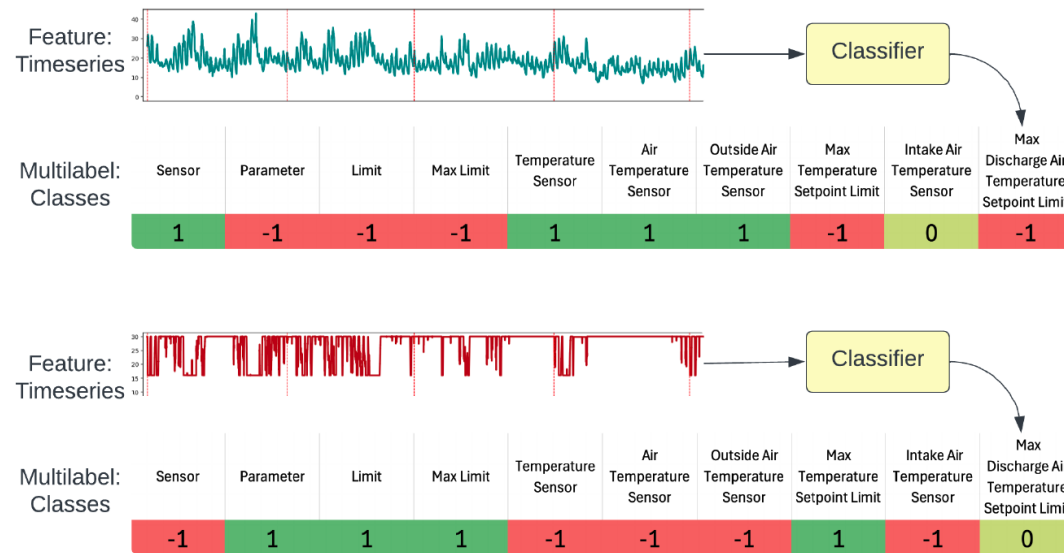


Figure 3: Visualisation of the multi-label timeseries classification task.

Zero-shot Forecasting

Table 5: Benchmark results on the zero-shot forecasting task. The columns refer to the training set, whereas the row represents the testing set.

| | BTS-A | | BTS-B | | BTS-C | |
|---------------------------|--------------|---------|---------|---------|---------|---------|
| | MAE | SMAPE | MAE | SMAPE | MAE | SMAPE |
| Previous Day Persistence | 0.5377 | 48.1539 | 0.4976 | 43.2985 | 0.5458 | 45.7014 |
| Previous Week Persistence | 0.6190 | 57.2713 | 0.5918 | 51.3867 | 0.6499 | 58.1922 |
| BTS-A | DLinear | N/A | 0.4324 | 35.9846 | 0.4262 | 36.2734 |
| | PatchTST | N/A | 0.3748 | 29.2570 | 0.3712 | 29.5552 |
| | Informer | N/A | 0.5968 | 49.2217 | 0.5920 | 51.9745 |
| | iTransformer | N/A | 0.4026 | 31.1924 | 0.3842 | 30.1102 |
| BTS-B | DLinear | 0.4940 | 41.2264 | N/A | 0.4206 | 35.3121 |
| | PatchTST | 0.4575 | 36.7689 | N/A | 0.3711 | 29.2135 |
| | Informer | 0.5233 | 45.9279 | N/A | 0.4592 | 39.7068 |
| | iTransformer | 0.4783 | 37.5907 | N/A | 0.3901 | 29.9940 |
| BTS-C | DLinear | 0.4858 | 40.7421 | 0.4158 | 34.1473 | N/A |
| | PatchTST | 0.4542 | 36.9451 | 0.3723 | 28.9325 | N/A |
| | Informer | 0.5213 | 46.6112 | 0.4602 | 39.7162 | N/A |
| | iTransformer | 0.4859 | 39.5158 | 0.4262 | 32.6550 | N/A |

BTS: Building Time-Series Dataset

Thank you

Official repo:

https://github.com/cruiseresearchgroup/DIEF_BTS/

We will launch a competition using this dataset.

