



PERCONA
LIVEONLINE
MAY 12 - 13th
2021

> whoami

Jorge Torres

CEO@MindsDB

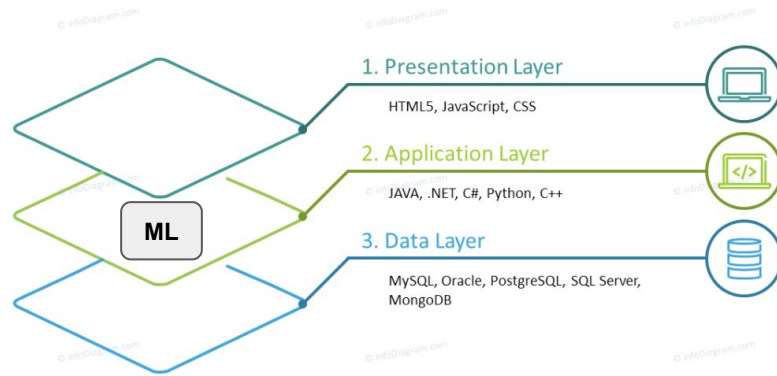
@tormmal

Machine Learning

Where does it belong best?

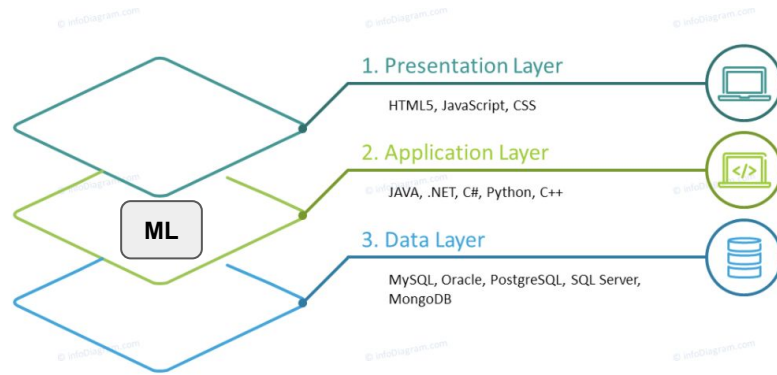
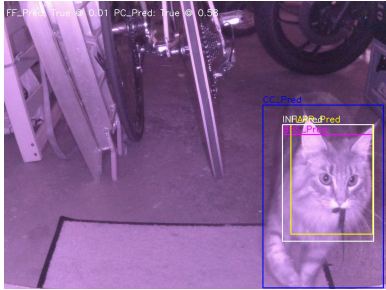
Application layer ML

When applying ML, does it have to live in the application stack?



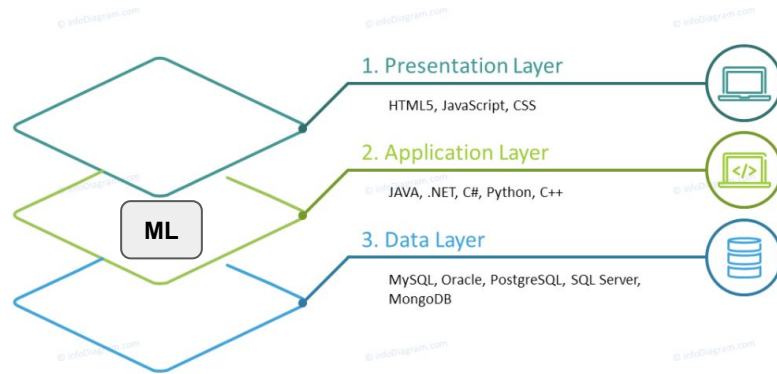
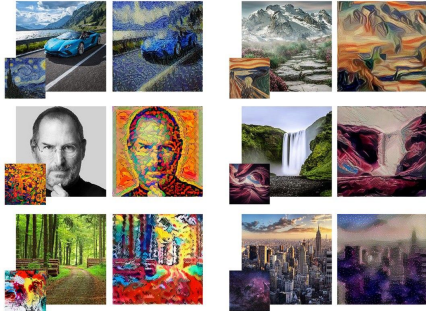
Application layer ML

When applying ML, does it have to live in the application stack?



Application layer ML

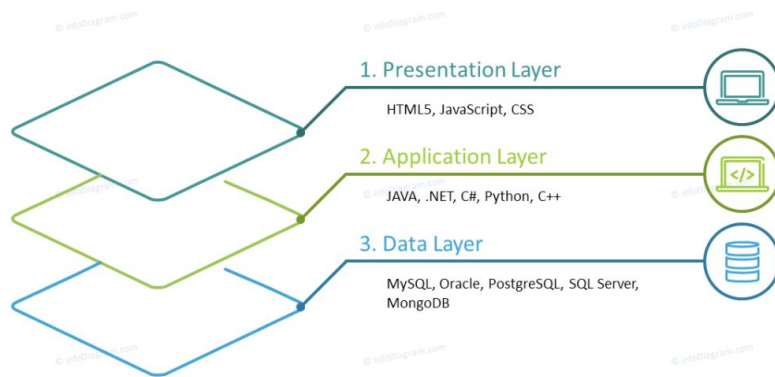
When applying ML, does it have to live in the application stack?



Machine Learning In the data layer

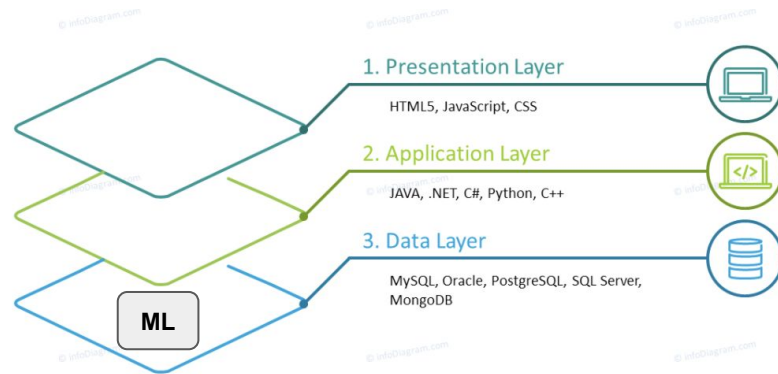
Data layer ML

When applying ML, can it live in the data layer?

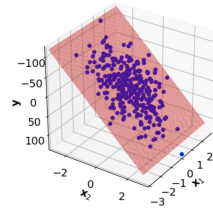
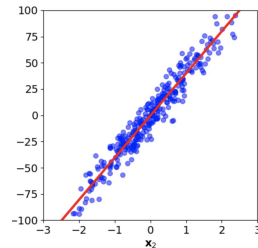
[illegible]

Data layer ML

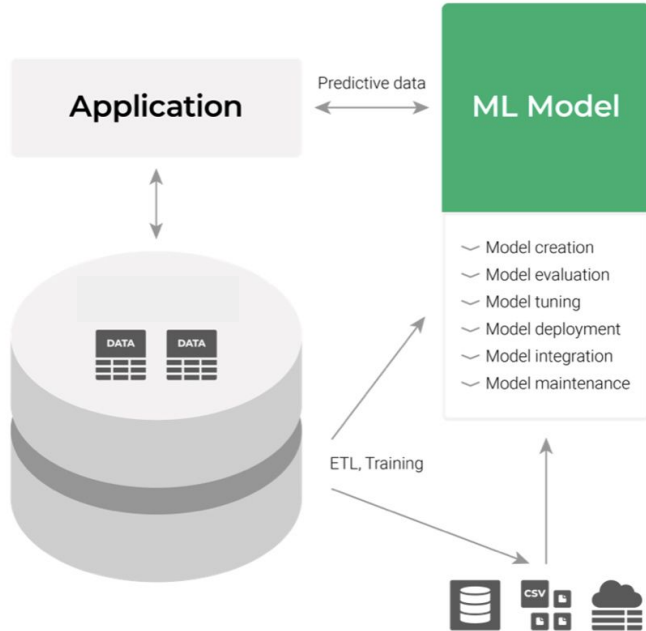
When applying ML, can it live in the data layer?



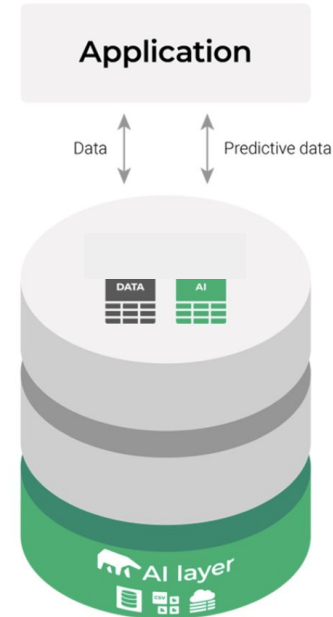
Entity	Age	Gender	Marital	Religion	Ethnicity	Education	Income	Health	Employment	Home	Travel	Spending	Assets	Liabilities	Net Worth	Score	Rank	Label	Color
John	35	M	Married	Christian	White	High School	\$45,000	Good	Full Time	Single	Yes	\$1,200	\$10,000	\$5,000	\$5,000	75	10	A	Blue
Jane	32	F	Married	Christian	White	College	\$50,000	Good	Full Time	Single	Yes	\$1,500	\$12,000	\$6,000	\$6,000	78	8	A	Blue
Emily	28	F	Single	Christian	White	College	\$60,000	Good	Full Time	Single	Yes	\$1,800	\$15,000	\$7,500	\$7,500	80	5	A	Blue
Michael	40	M	Married	Christian	White	College	\$55,000	Good	Full Time	Single	Yes	\$1,600	\$13,000	\$6,500	\$6,500	77	9	A	Blue
Sarah	38	F	Married	Christian	White	College	\$52,000	Good	Full Time	Single	Yes	\$1,400	\$11,000	\$5,500	\$5,500	76	11	A	Blue
David	30	M	Single	Christian	White	College	\$65,000	Good	Full Time	Single	Yes	\$2,000	\$18,000	\$9,000	\$9,000	82	3	A	Blue
Robert	45	M	Married	Christian	White	College	\$58,000	Good	Full Time	Single	Yes	\$1,700	\$14,000	\$7,000	\$7,000	79	7	A	Blue
Michelle	33	F	Married	Christian	White	College	\$53,000	Good	Full Time	Single	Yes	\$1,500	\$12,000	\$6,000	\$6,000	77	12	A	Blue
Christopher	37	M	Married	Christian	White	College	\$56,000	Good	Full Time	Single	Yes	\$1,600	\$13,000	\$6,500	\$6,500	78	6	A	Blue
Amanda	29	F	Single	Christian	White	College	\$62,000	Good	Full Time	Single	Yes	\$1,900	\$16,000	\$8,000	\$8,000	81	4	A	Blue
James	42	M	Married	Christian	White	College	\$57,000	Good	Full Time	Single	Yes	\$1,700	\$14,000	\$7,000	\$7,000	79	13	A	Blue
Stephanie	31	F	Married	Christian	White	College	\$54,000	Good	Full Time	Single	Yes	\$1,600	\$13,000	\$6,500	\$6,500	78	14	A	Blue
Kevin	36	M	Married	Christian	White	College	\$59,000	Good	Full Time	Single	Yes	\$1,800	\$15,000	\$7,500	\$7,500	80	15	A	Blue
Nicole	27	F	Single	Christian	White	College	\$63,000	Good	Full Time	Single	Yes	\$2,000	\$19,000	\$9,500	\$9,500	83	2	A	Blue
Brandon	41	M	Married	Christian	White	College	\$56,000	Good	Full Time	Single	Yes	\$1,700	\$14,000	\$7,000	\$7,000	79	16	A	Blue
Heather	34	F	Married	Christian	White	College	\$51,000	Good	Full Time	Single	Yes	\$1,400	\$11,000	\$5,500	\$5,500	76	17	A	Blue
Gregory	39	M	Married	Christian	White	College	\$54,000	Good	Full Time	Single	Yes	\$1,600	\$13,000	\$6,500	\$6,500	78	18	A	Blue
Christina	26	F	Single	Christian	White	College	\$64,000	Good	Full Time	Single	Yes	\$2,100	\$20,000	\$10,000	\$10,000	84	1	A	Blue
Anthony	43	M	Married	Christian	White	College	\$57,000	Good	Full Time	Single	Yes	\$1,700	\$14,000	\$7,000	\$7,000	79	19	A	Blue
Kimberly	30	F	Married	Christian	White	College	\$52,000	Good	Full Time	Single	Yes	\$1,400	\$11,000	\$5,500	\$5,500	76	20	A	Blue
Timothy	35	M	Married	Christian	White	College	\$55,000	Good	Full Time	Single	Yes	\$1,600	\$13,000	\$6,500	\$6,500	78	21	A	Blue
Rebecca	28	F	Single	Christian	White	College	\$61,000	Good	Full Time	Single	Yes	\$1,900	\$16,000	\$8,000	\$8,000	81	22	A	Blue
Benjamin	44	M	Married	Christian	White	College	\$58,000	Good	Full Time	Single	Yes	\$1,700	\$14,000	\$7,000	\$7,000	79	23	A	Blue
Victoria	32	F	Married	Christian	White	College	\$53,000	Good	Full Time	Single	Yes	\$1,500	\$12,000	\$6,000	\$6,000	77	24	A	Blue
Patrick	37	M	Married	Christian	White	College	\$56,000	Good	Full Time	Single	Yes	\$1,700	\$14,000	\$7,000	\$7,000	79	25	A	Blue
Christine	29	F	Single	Christian	White	College	\$62,000	Good	Full Time	Single	Yes	\$1,900	\$16,000	\$8,000	\$8,000	81	26	A	Blue
Joseph	40	M	Married	Christian	White	College	\$55,000	Good	Full Time	Single	Yes	\$1,600	\$13,000	\$6,500	\$6,500	78	27	A	Blue
Stephanie	31	F	Married	Christian	White	College	\$54,000	Good	Full Time	Single	Yes	\$1,600	\$13,000	\$6,500	\$6,500	78	28	A	Blue
Kevin	36	M	Married	Christian	White	College	\$59,000	Good	Full Time	Single	Yes	\$1,800	\$15,000	\$7,500	\$7,500	80	29	A	Blue
Nicole	27	F	Single	Christian	White	College	\$63,000	Good	Full Time	Single	Yes	\$2,000	\$19,000	\$9,500	\$9,500	83	30	A	Blue



Application layer ML vs Data layer ML



VS



How does it work?

AI Tables

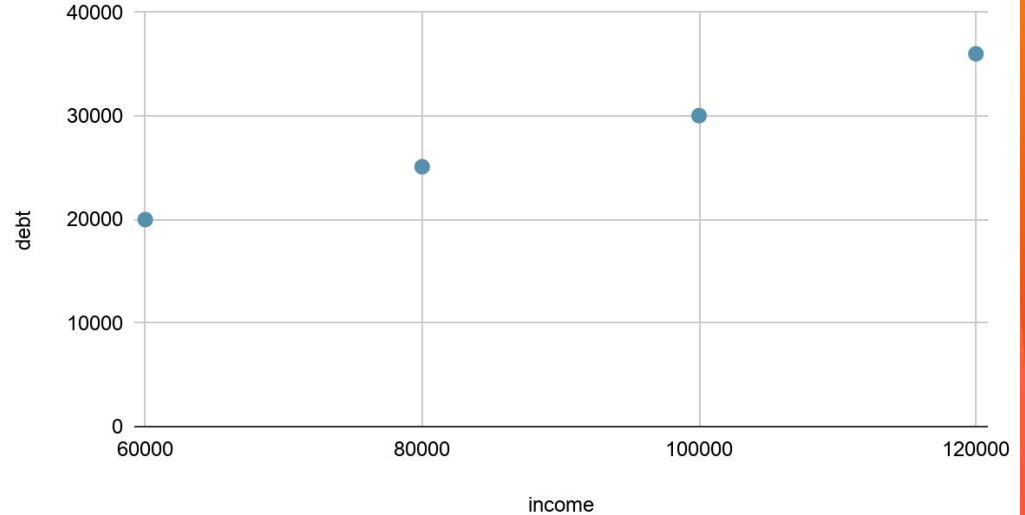
ML Predictive models as Database tables

Simple Example, from DB Tables to ML model

```
SELECT income, debt  
FROM income_table
```

income	debt
60000	20000
80000	25100
100000	30040
120000	36010

debt vs. income



DB Tables and queries

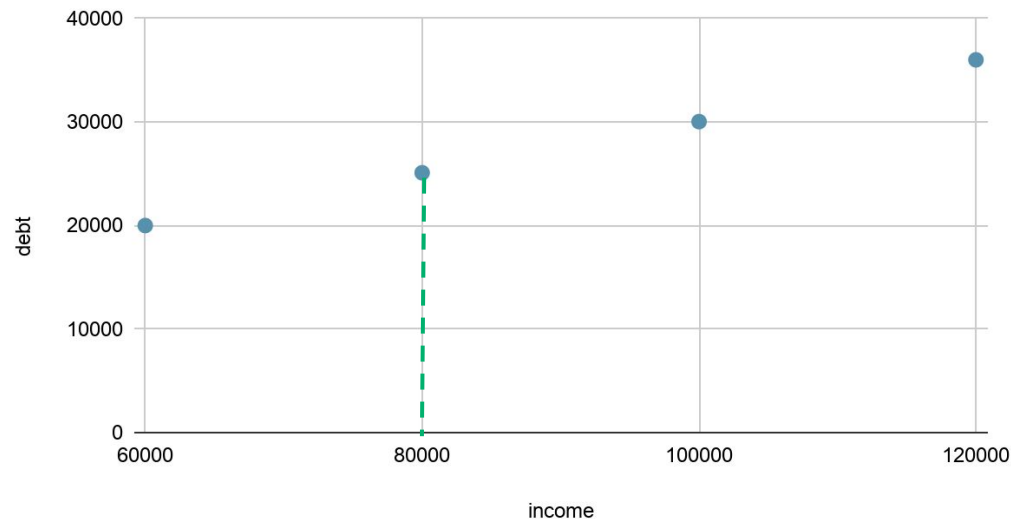
income_table

income	debt
60000	20000
80000	25100
100000	30040
120000	36010

```
SELECT income, debt FROM income_table  
WHERE income = 80000
```

income	debt
80000	25100

debt vs. income



You could query the database for information in this table, and if your search criteria has a match, you get results.

DB queries and mismatches

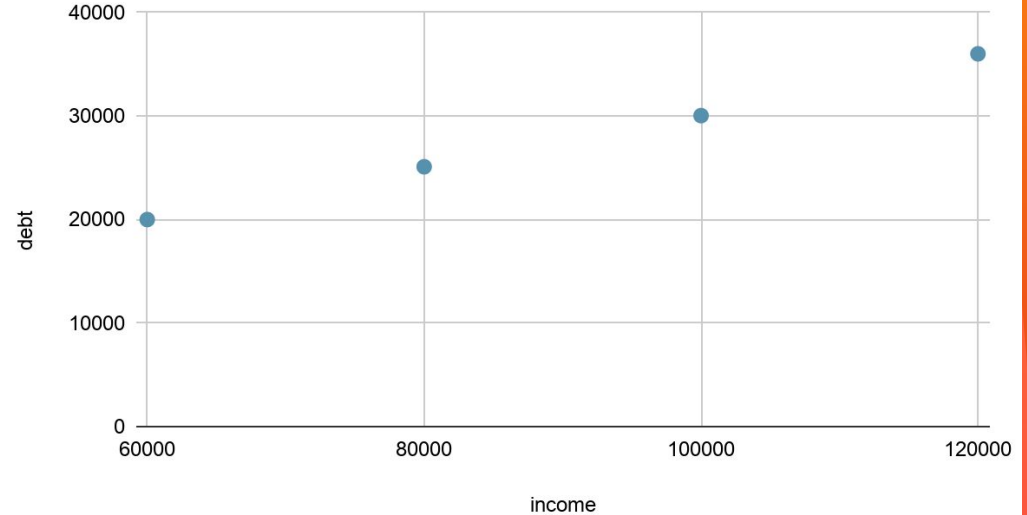
income_table

income	debt
60000	20000
80000	25100
100000	30040
120000	36010

```
SELECT income, debt FROM income_table  
WHERE income = 90000
```

income	debt
90000	NULL

debt vs. income



Navigation icons: back, forward, search, etc.

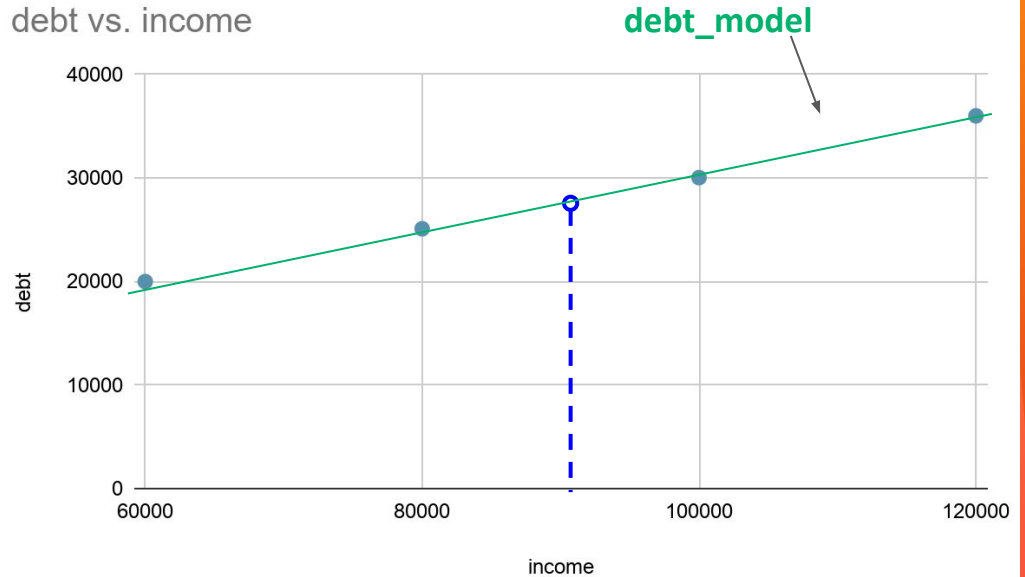
However, if there is no match for your search criteria you get empty results.
Even if your search criteria is close to some data.

Machine Learning as DB Tables

```
SELECT
  income, debt, predicted_debt
FROM
  debt_model
WHERE
  income = 90120
```

income	debt
90120	28010

debt vs. income



There are hard problems in data layer ML!

Multivariate time series forecasting with MindsDB

> whoami

Patricio Cerda-Mardini

Machine Learning Research Engineer

@paxcema



Example

Let's consider electrical power consumption forecasting

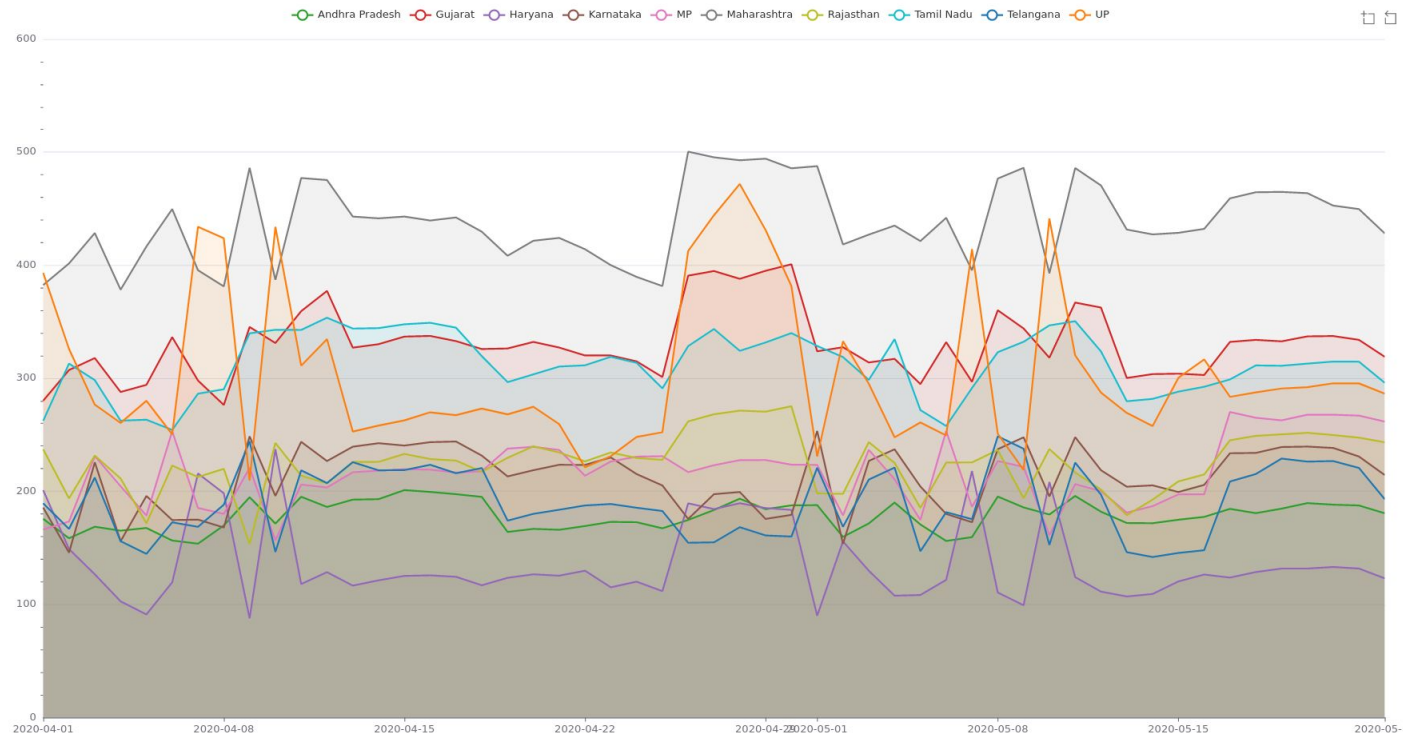
	States	Regions	latitude	longitude	Dates	Usage
0	Punjab	NR	31.519974	75.980003	02/01/2019 00:00:00	119.9
1	Haryana	NR	28.450006	77.019991	02/01/2019 00:00:00	130.3
2	Rajasthan	NR	26.449999	74.639981	02/01/2019 00:00:00	234.1
3	Delhi	NR	28.669993	77.230004	02/01/2019 00:00:00	85.8
4	UP	NR	27.599981	78.050006	02/01/2019 00:00:00	313.9
5	Uttarakhand	NR	30.320409	78.050006	02/01/2019 00:00:00	40.7



Source:

[kaggle.com/twinkle0705/
state-wise-power-consumption-in-india](https://kaggle.com/twinkle0705/state-wise-power-consumption-in-india)

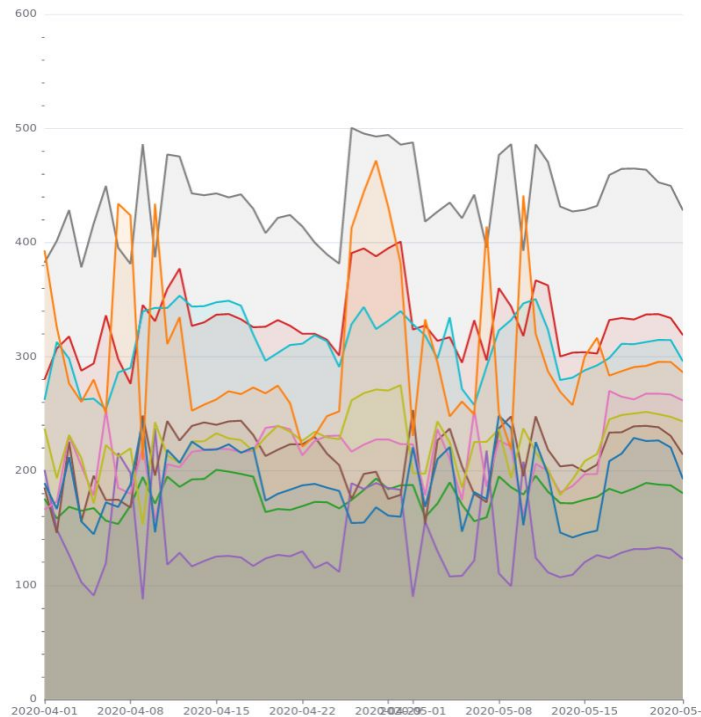
Example



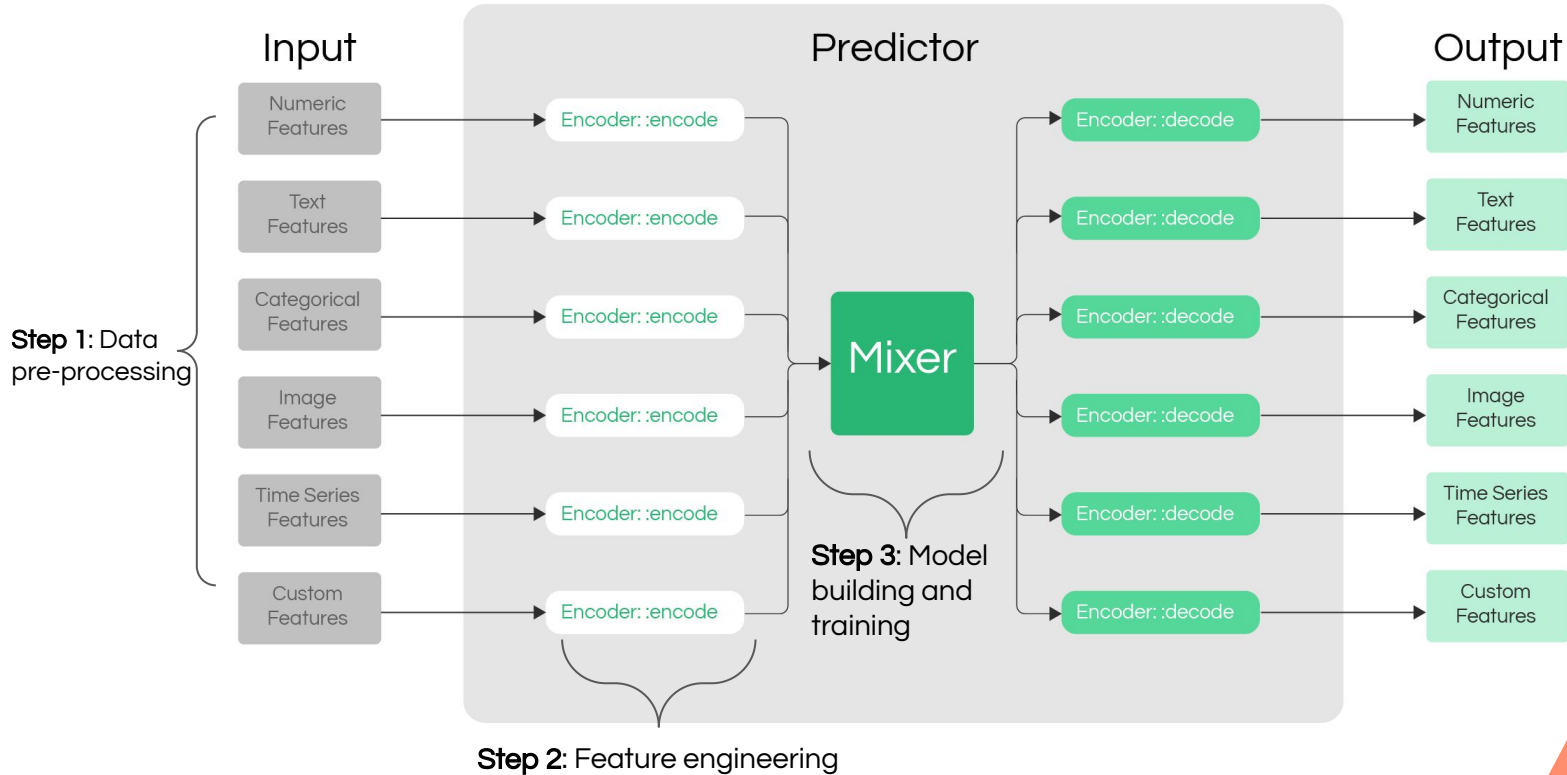
Time series forecasting can be challenging

1. Data pipeline instancing
2. High group cardinality
3. Efficient use of resources

MindsDB automates this process

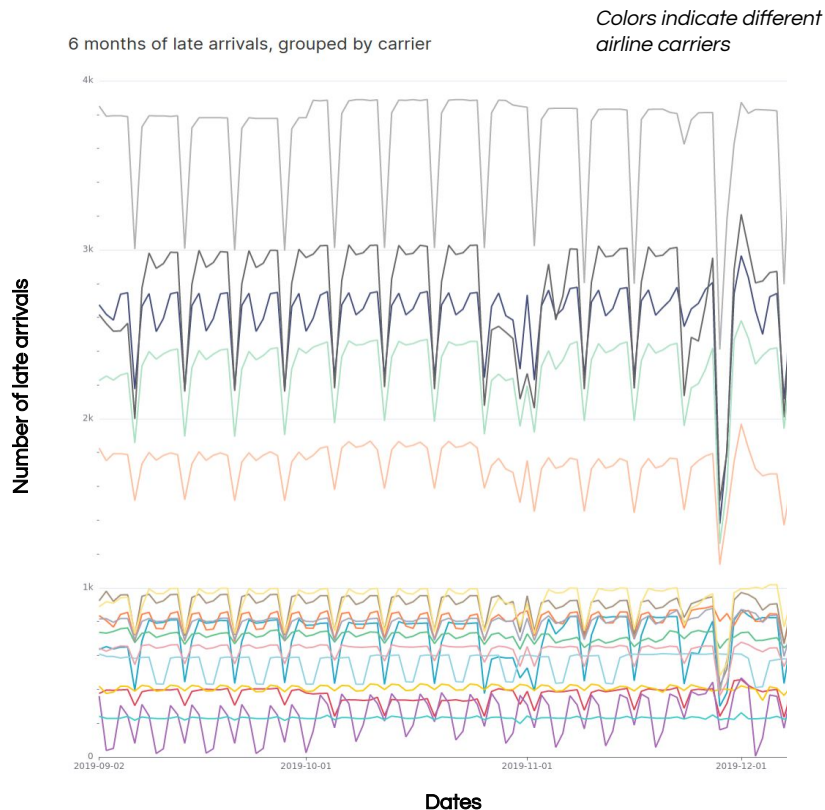


Flexible encoder-mixer philosophy

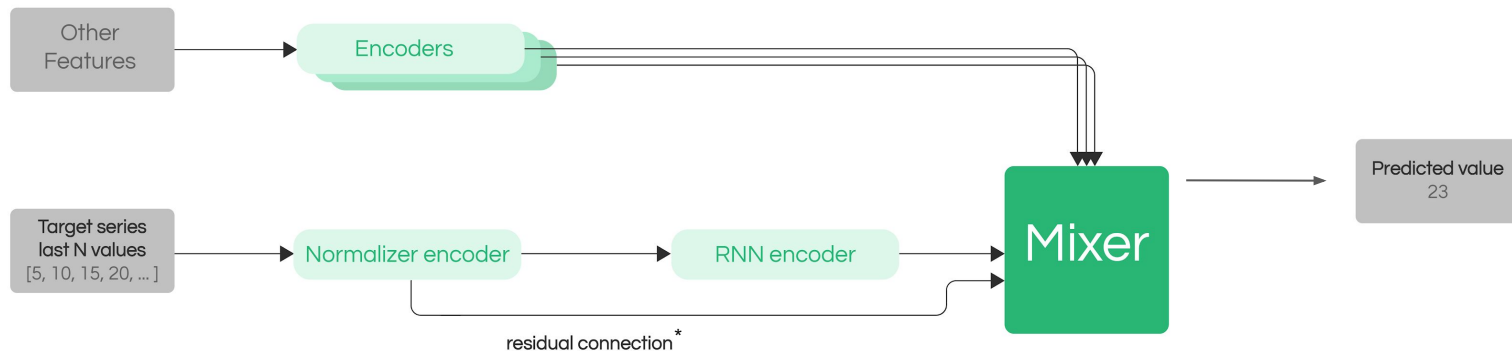


Dynamic Normalization

1. Store statistics for each series (one per group combination)
2. Normalize input using these stats
3. Mixer learns to predict normalized values



Mixers



- Neural network mixer for time series has two streams
 - a. learned autoregressive process yields base prediction
 - b. secondary stream handles for fine-tuning
- Gradient booster mixer uses LightGBM. MindsDB supports Optuna for stepwise hyperparameter search.

Example - SQL usage

Training:

```
INSERT INTO predictors( name,  
                        predict,  
                        select_data_query,  
                        Training_options )  
  
VALUES ( 'PowerConsumption',  
        'Usage',  
        'SELECT * FROM training_data;',  
        '{"timeseries_settings": {  
          "order_by": ["Dates"],  
          "group_by": ["States"],  
          "window": 10  
        }}')
```

Example - SQL usage

Querying:

1) Conditional single prediction

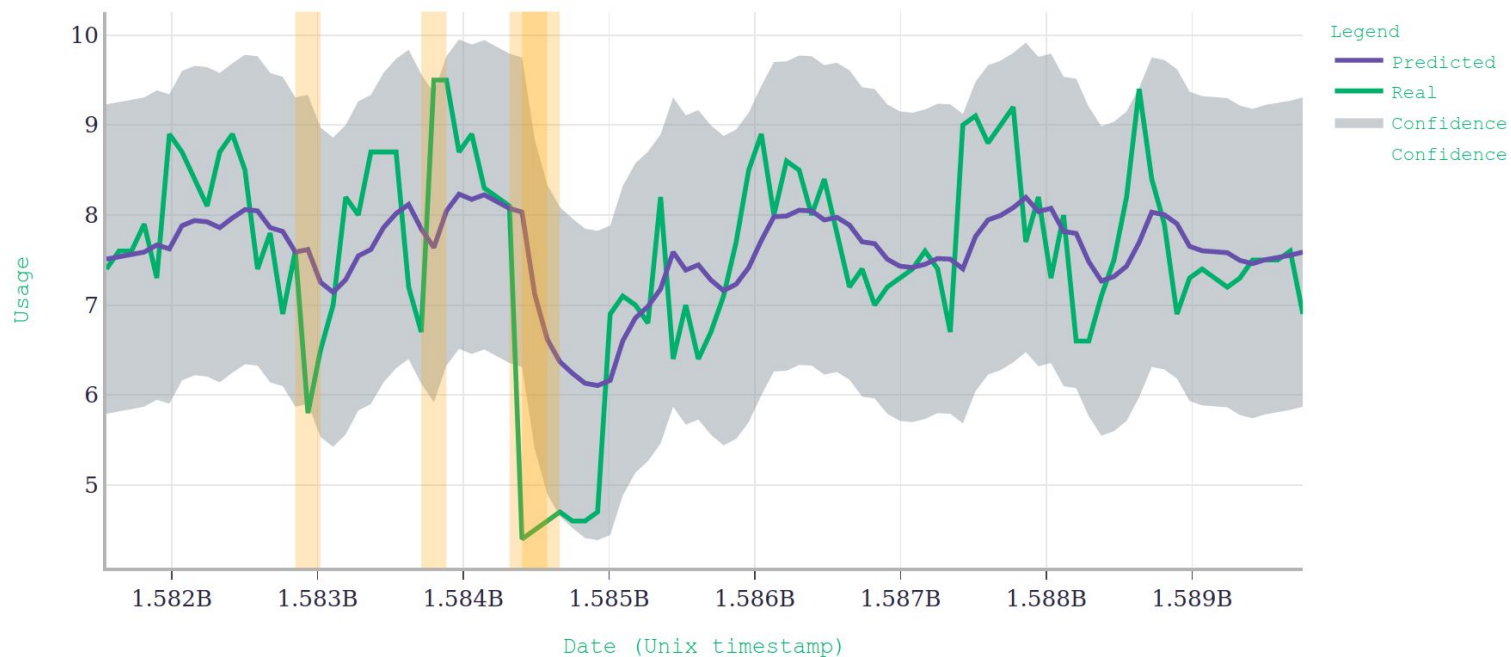
```
SELECT Usage FROM mindsdb.PowerConsumption WHERE Dates =  
"2021/03/14 12:34:56 ";
```

2) Batch prediction

```
SELECT d.Dates, d.Usage as PrevUsage, p.Usage FROM  
data.test  
AS d LEFT JOIN mindsdb.PowerConsumption AS p ON 1=1;
```

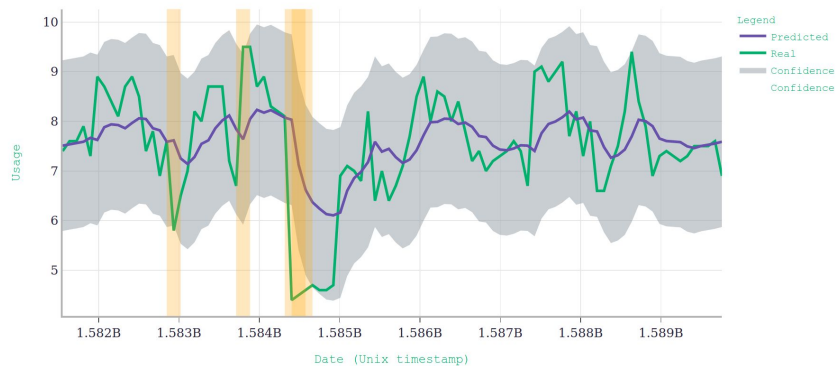
Single group forecasting

MindsDB t+1 forecast for State Pondy



Multivariate forecasting

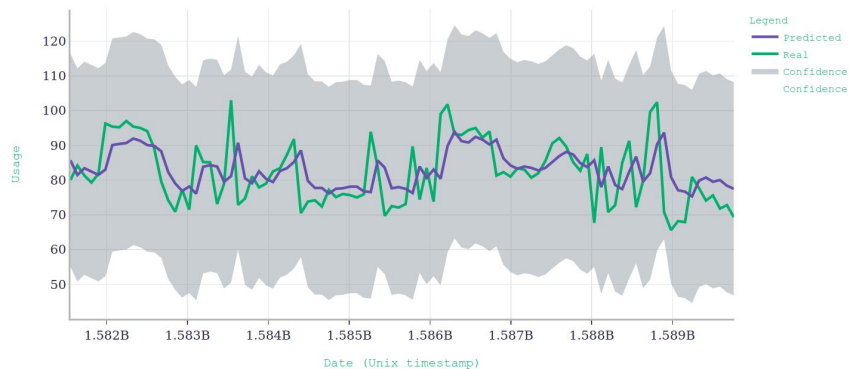
MindsDB t+1 forecast for State Pondy



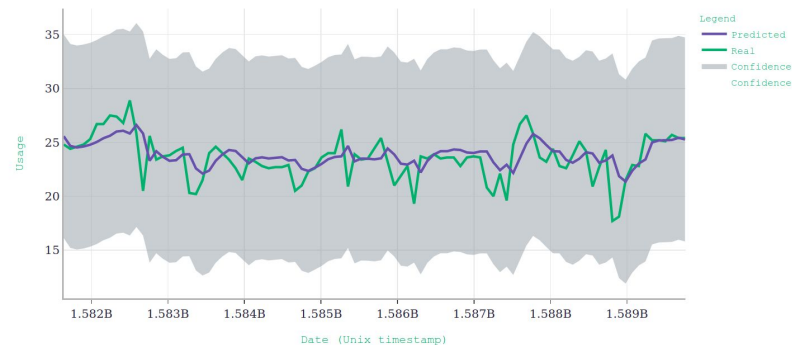
MindsDB t+1 forecast for State Kerala



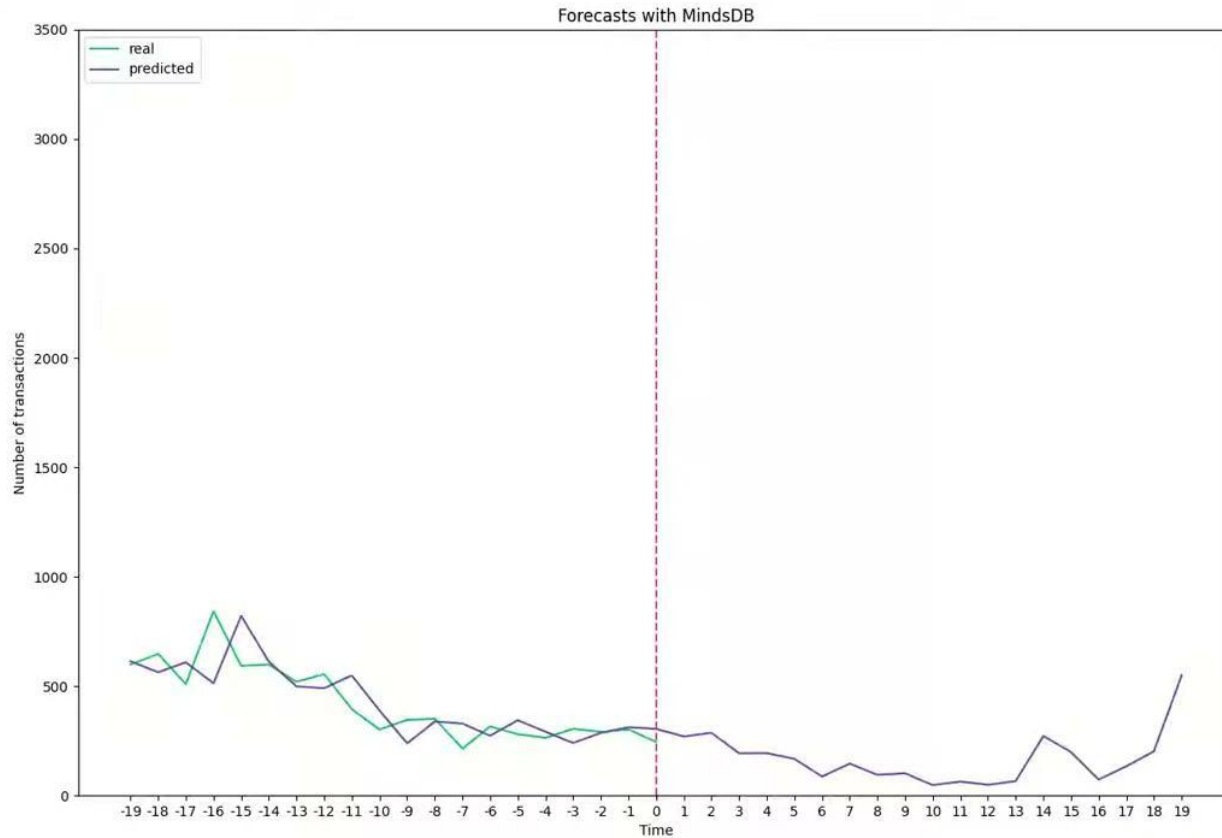
MindsDB t+1 forecast for State Chhattisgarh



MindsDB t+1 forecast for State Jharkhand



Visualized forecasting







Future Work

- Predicting data streams (e.g. Redis, Kafka)
- Improving forecasts for long horizons with multiple imputation
- Detecting gradual anomalies
- Modin integration

Questions?

You can find us at:

- @tormal 
- @paxcema   



/mindsdb/mindsdb

THANK YOU !



PERCONA
LIVEONLINE
MAY 12 - 13th
2021