

# Self-supervised Learning for Semi-supervised Time Series Classification

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# Content

- Motivation
- Problem description
- Related work
- Method
- Experimental settings and results
- Conclusion
- My thoughts

# Motivation

- High cost to label large datasets
- Gathering large amounts of time series data is often trivial
- So, less labeling \* large datasets = winning

# Problem description

- Accurately predict classes of time series classification problems where there are few labeled samples using deep learning

# Related work

## Seminal work

- Nearest neighbor classifiers(with meta-feature distance)
- Clustering
- Graphs(distance functions and label propagation)
- Shapelets

## Recent work

- Tasks inherent in the data itself

## Most related work

- Multi-task self-supervised network

# Method

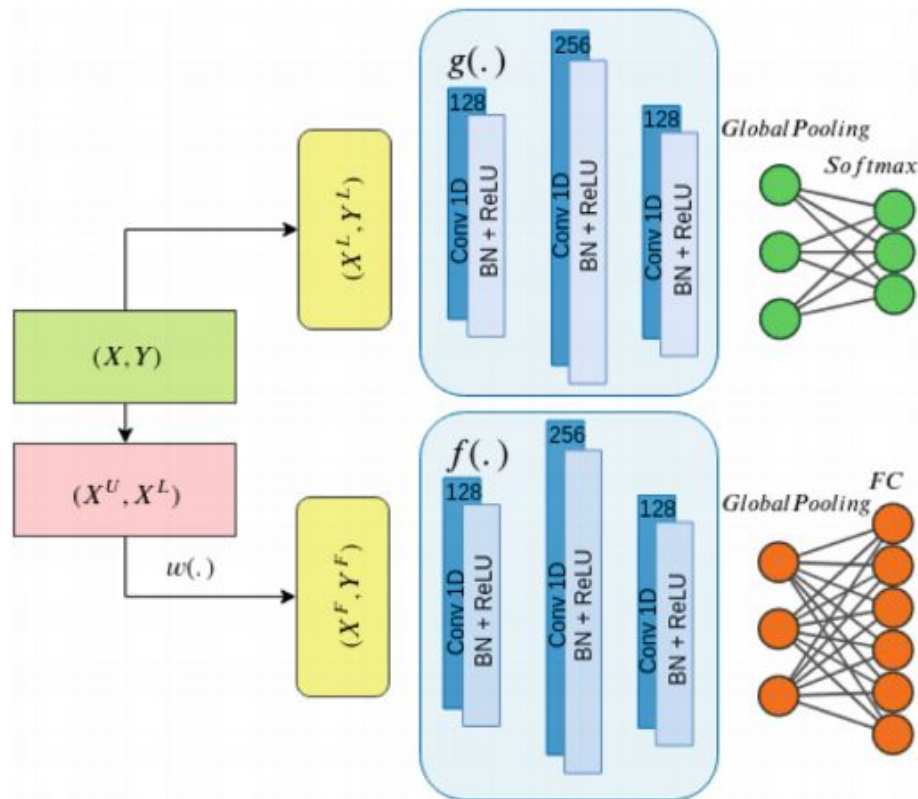
## Data preparation

Splitting univariate time series dataset  $X$ ;

- $X^L$  -> Labeled set
- $X^U$  -> Unlabeled set

Sliding window function  $w(\cdot)$ ;

- Made up by stride  $s$  and horizon  $h$
- Builds forecasting samples  $X^F$



# Method

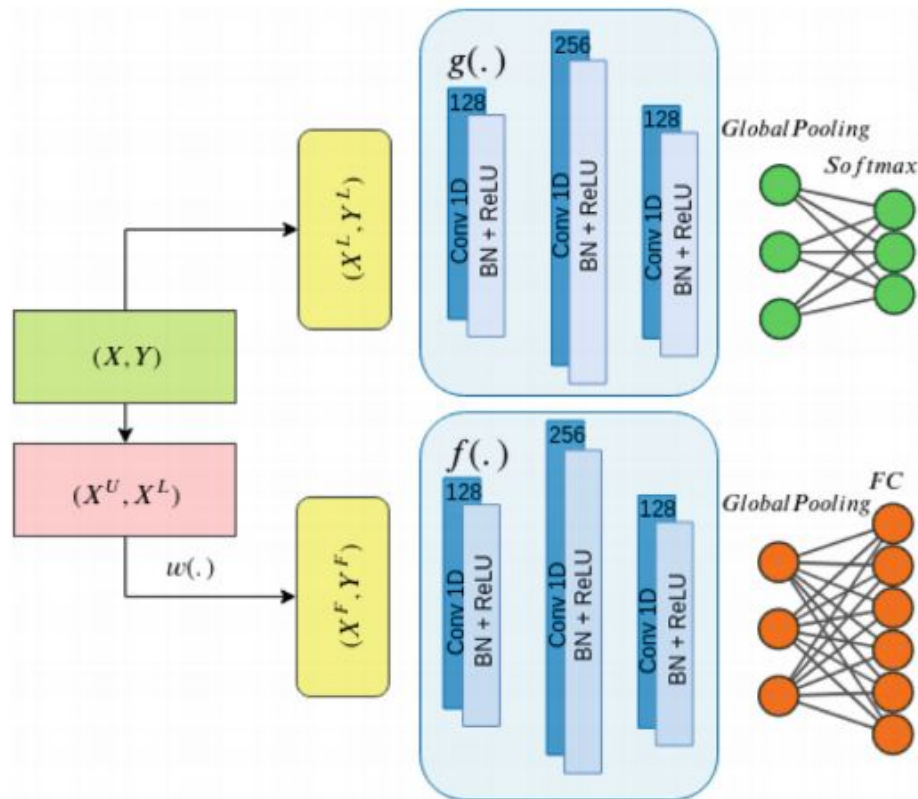
## Objective

Forecasting function  $f(\cdot)$

Classification function  $g(\cdot)$

$$Y^F = f(X^F)$$

$$Y^L = g(X^L)$$



# Method

## Loss functions

Forecasting loss function  $L_f(.)$

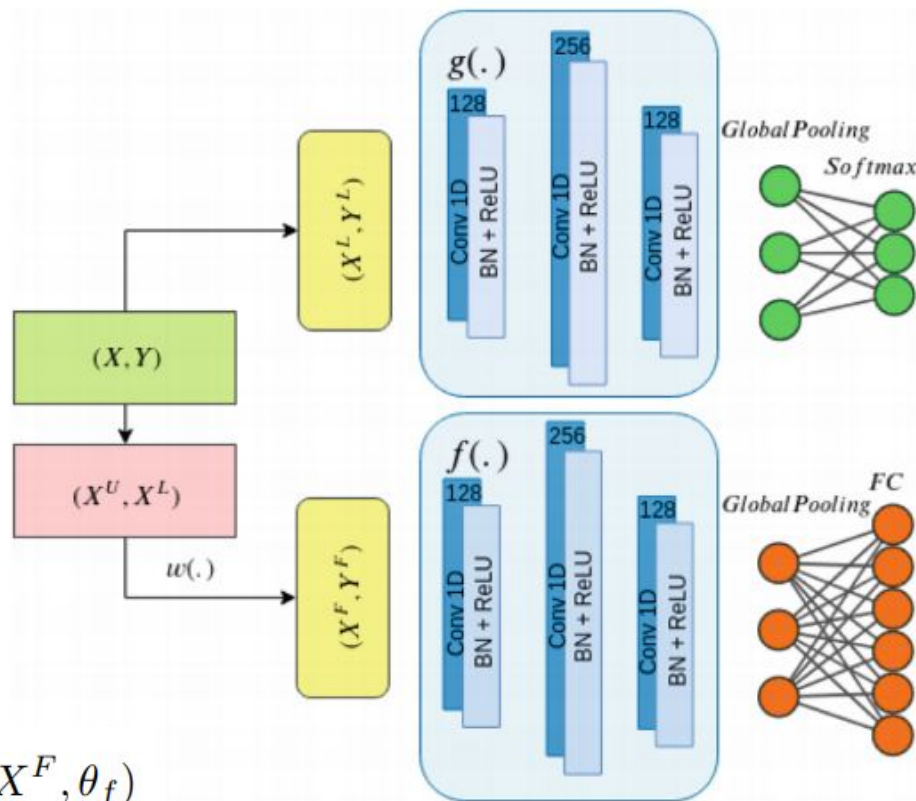
$$L_f(X^F, \theta_f) = \frac{1}{n \times m \times h} \sum_i^n \sum_j^m \sum_t^h (y_{jt}^i - \hat{y}_{jt}^i)^2$$

Classification loss function  $L_c(.)$

$$L_c(X^L, \theta_c) = -\frac{1}{l} \sum_i^l \log \left( \frac{e^{\hat{y}_{i=c}}}{\sum_j^C e^{\hat{y}_i}} \right)$$

Combined loss function

$$L_{MTL}(X^F, \theta_f, X^L, \theta_c) = L_c(X^L, \theta_c) + \lambda L_f(X^F, \theta_f)$$

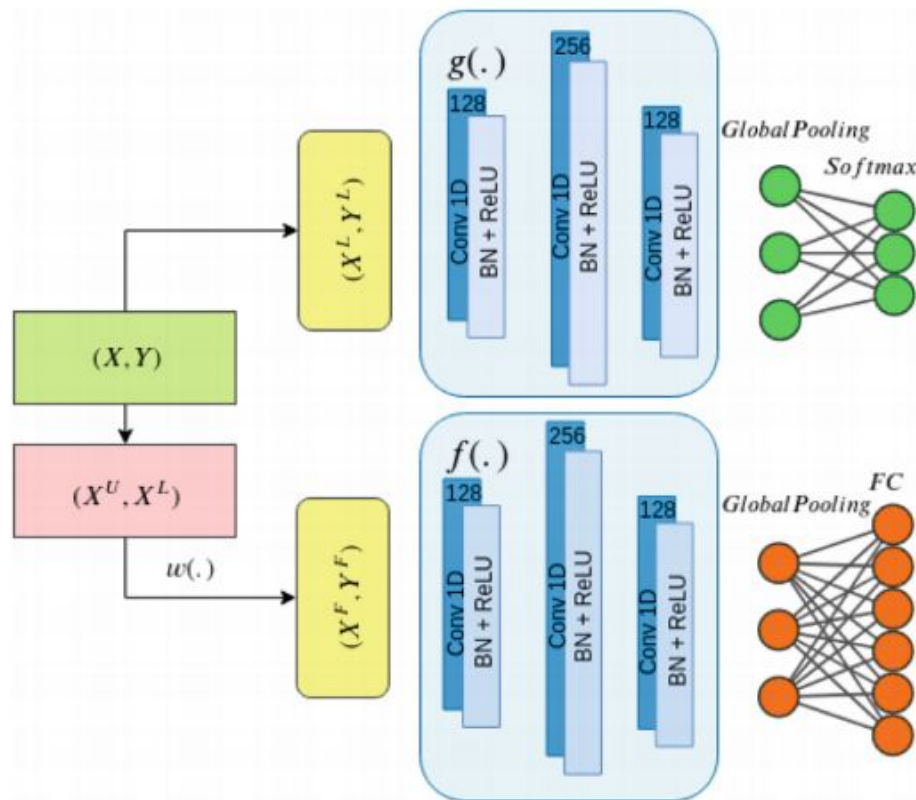




# Method

## Further elaboration

- Forecasting as an auxiliary task
- Horizon and stride
- Multi-task learning
- Key challenges
- Intuition?



# Experimental settings and results

# Baselines

- Wei's method
- DTW-D
- SUCCESS
- Xu's method
- Bag-of-words
- SSSL
- Base
- $\Pi$ -model
- Transfer learning

# Results

	Coffee	CBF	ECG	Face-Four	OSULf	Italy-Power	Light.2	Light.7	Gun-Point	Trace	Word-Syn	Olive-Oil	Star-Light
#	56	930	200	112	442	1096	121	143	200	200	905	60	9236
<i>C</i>	2	3	2	4	6	2	2	7	2	4	25	4	3
<i>T</i>	286	128	96	350	427	24	637	319	150	275	270	570	1024

Datasets	Results verbatim from table in [17]						Proposed			
	Wei.	DTW-D	SUC.	Xu.	BoW	SSSL	Base	II	Tr.	MTL
Coffee	0.571	0.601	0.632	0.588	0.620	0.792	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>
CBF	0.995	0.833	0.997	0.921	0.873	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	0.784	<b>1.0</b>
cre ECG	0.763	0.953	0.775	0.819	0.955	0.793	0.9	0.875	0.9	<b>0.975</b>
FaceFour	0.818	0.782	0.800	0.833	0.744	0.851	0.913	0.913	0.739	<b>0.957</b>
OSULf	0.468	0.701	0.534	0.642	0.685	0.835	0.977	0.977	0.460	<b>0.978</b>
ItalyPower	0.934	0.664	0.924	0.772	0.813	0.941	0.986	0.986	0.959	<b>0.991</b>
Light.2	0.658	0.641	0.683	0.698	0.721	0.813	0.92	0.84	0.88	<b>0.92</b>
Light.7	0.464	0.503	0.471	0.511	0.677	0.796	0.758	0.689	0.482	<b>0.828</b>
GunPoint	0.925	0.711	0.955	0.729	0.925	0.824	<b>1.0</b>	<b>1.0</b>	0.825	<b>1.0</b>
Trace	0.950	0.801	<b>1.0</b>	0.788	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>
WordSyn	0.590	0.863	0.618	0.639	0.795	<b>0.875</b>	0.497	0.491	0.342	0.519
OliveOil	0.633	0.732	0.617	0.639	0.766	0.776	0.916	<b>1.0</b>	0.833	<b>1.0</b>
StarLight	0.860	0.743	0.800	0.755	0.851	0.872	0.982	0.983	<b>1.0</b>	0.991

# Settings used

Datasets	$s$ : 0.05		0.1		0.2	
	$h$ : 0.1	0.2	0.1	0.2	0.1	0.2
Coffee	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>
CBF	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>
ECG	0.950	0.9	0.925	0.9	<b>0.975</b>	0.875
FaceFr.	0.913	0.913	0.870	<b>0.957</b>	<b>0.957</b>	0.913
OSULf.	0.966	0.966	<b>0.978</b>	0.955	<b>0.978</b>	0.955
ItalyPower	0.986	<b>0.991</b>	0.986	0.986	0.982	<b>0.991</b>
Light.2	0.840	<b>0.920</b>	0.840	0.880	0.880	0.880
Light.7	<b>0.828</b>	<b>0.828</b>	0.759	0.759	0.793	0.759
GunPoint	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>
Trace	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>
WordSyn.	0.497	<b>0.519</b>	0.508	0.497	0.503	0.508
OliveOil	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>	<b>1.0</b>
StarLight	0.983	0.983	0.99	0.97	0.983	<b>0.991</b>

# Conclusion

- Novel self-supervised task
- More accurate than a majority of baselines on benchmark datasets
- Multivariate time series next
- Github repo available for reproducibility

# My thoughts

- Liked the concept
- Not too hard to read
- Maybe relevant to my thesis