Data-Driven Option Pricing using Single and Multi-Asset Supervised Learning

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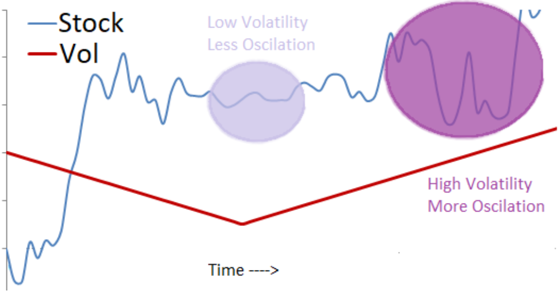
[1] Coauthored by Sharan Rajani and Atharva Tanksale

Risky Asset

The financial market has inherent uncertainty.
If oscillation increases, we say volatility factor is more.



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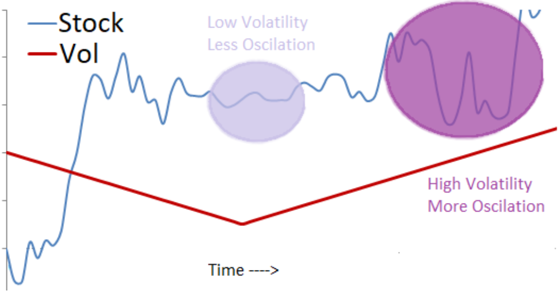

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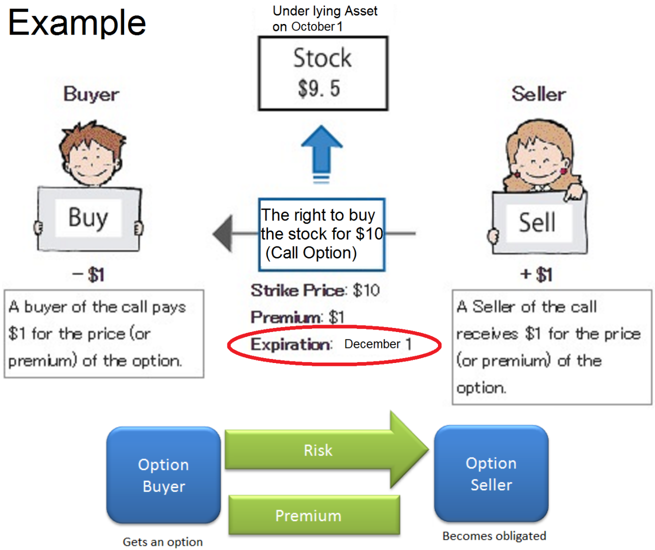
What is a Derivative Instrument?



Theoretical vs Data-Driven Approaches

- The fair price of an option contract depends on the current anticipation of the future dynamics of the underlying asset.
- The success or failure of theoretical option pricing and hedging is closely tied to the success in capturing the dynamics of the underlying asset's price movements.
- Simplified assumptions of theoretical models do not match reality.
- Complicated theoretical models are hard to calibrate.
- Since this is a hard problem, adoption of data-driven approaches in pricing option contracts is gaining attention with the advent of superior computational power and advancements in statistical learning techniques.

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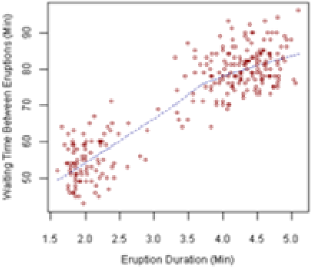

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- Input $X^{(j)} \in \mathcal{E}$ is associated with a label $Y^{(j)} \in \mathcal{C}$.
- The "best" $f : X^{(j)} \mapsto Y^{(j)}$ is sought for out of all the possible mappings. But Y are noisy.
- The algorithm instead attempts to find the best possible score distribution $P : \mathcal{E} \to \mathcal{P}(\mathcal{C})$.
- The mapping/model is assessed by an "objective/loss function".
- Accomplished with diverse algorithms with different approches.

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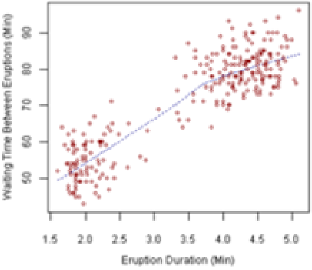

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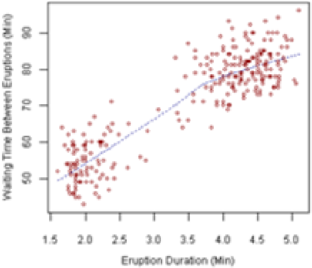

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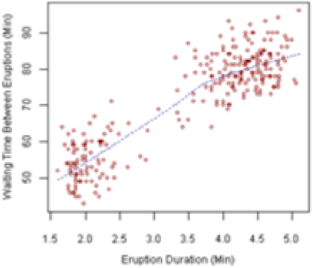

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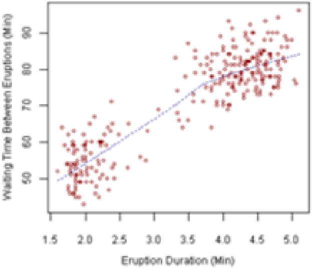

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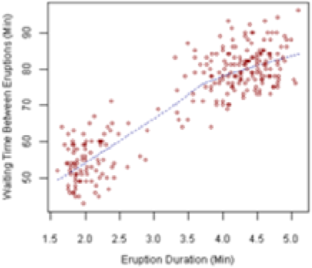

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ML Approach in Option Pricing

Q. Find European call option price as a function of current stock. The general shape of the curve is intuitively known.

Figure : Call option price function with different time to maturity

We need to find the exact values of the option price function.

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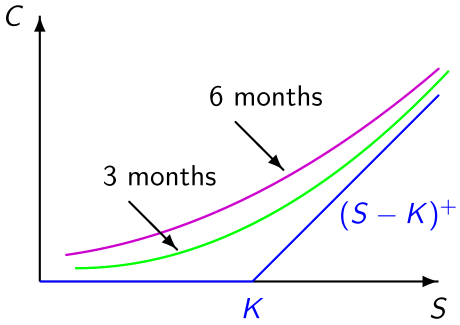

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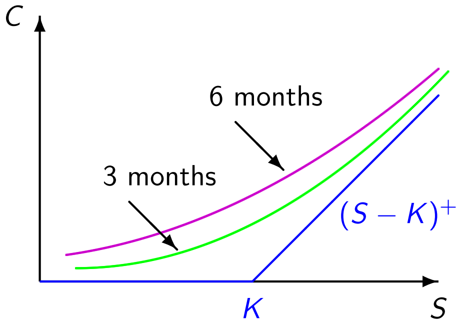

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Data

Symbol	Date	Expiry	Option Type	Strike Price	Open	High	Low	Close	LTP	Settle Price	No. of contracts	Turnover in Lacs	Premium Turnover in Lacs	Open Int	Change in OI	Underlying Value
NIFTY	01-Jan-2014	30-Jan-2014	CE	7000	0.95	1.10	0.85	1.00	1.10	1.00	2444	8555.16	-	811950	10750	6301.65
NIFTY	01-Jan-2014	30-Jan-2014	CE	7050	0.00	0.00	0.00	0.25	0.25	1.40	0	0.00	-	350	0	6301.65
NIFTY	01-Jan-2014	30-Jan-2014	CE	6800	3.15	3.95	2.85	3.60	3.90	3.60	15039	51157.12	-	1403700	12400	6301.65
NIFTY	01-Jan-2014	30-Jan-2014	CE	6850	0.00	0.00	0.00	2.75	2.75	6.85	0	0.00	-	15350	0	6301.65
NIFTY	01-Jan-2014	30-Jan-2014	CE	6900	1.40	1.85	1.30	1.55	1.85	1.55	9156	31594.85	-	778250	39950	6301.65

Figure : Snapshot of the Unfiltered option Dataset

- Daily data of price of call options on NIFTY50 and BANKNIFTY index for the years 2015 – 2018 (4 years).
- Source: NSE website's contract wise archive section[2].

[2] The data can be accessed using the link - https://www1.nseindia.com/products/content/derivatives/equities/historical_fo.htm

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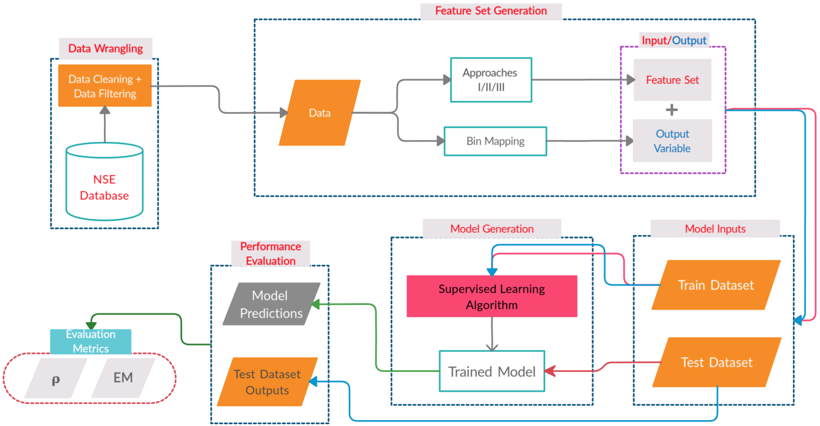
Data

Dataset	NIFTY50	BANKNIFTY
Raw	1072695	350186
Filtered	13516	20414
Train	10837	13622
Test	2679	6792

Table : Train/Test Split: Dataset Sizes

Process Flowchart



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Option Price: Numeral values vs Ordinal Category

- we believe that no real market is complete.
- In other words, a random payoff such as an option contract may have multiple fair prices
- So, a single predicted price is more confusing than convincing.
- We therefore define the output variable in a manner that conveys a range of fair prices.
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Output Category

- Scale-free target: $100 \times \frac{C}{K}$.
- We divide the range of outputs into non-overlapping "bins" and select the "embracing" bin as the output variable.
- Determining the width of the bins is challenging.

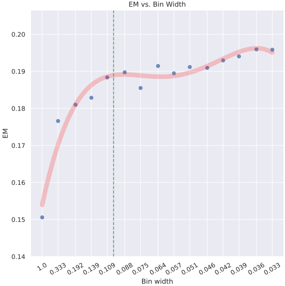

Figure : Binning insensitivity of the performance measure

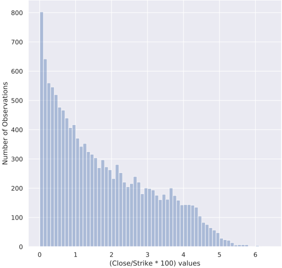

Figure : Histogram of $100 \times \frac{C}{K}$ values for NIFTY50 contracts

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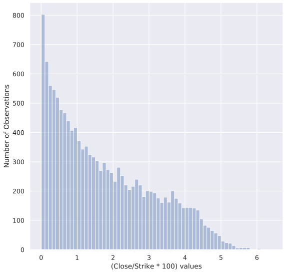

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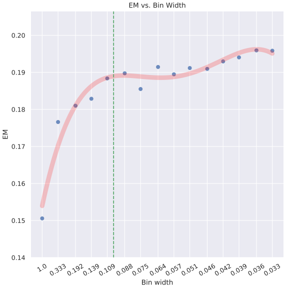

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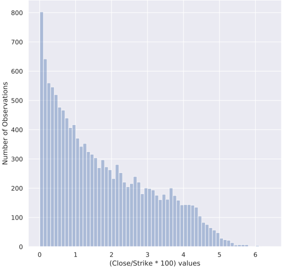

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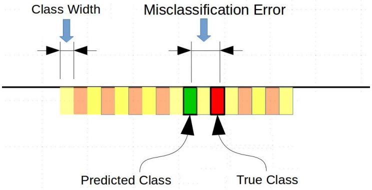
Performance Measures

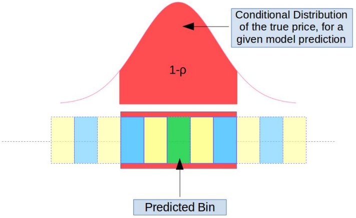
- Error Metric:-

$$\text{EM} = \left(\frac{w}{T} \sum_{i=1}^{i=T} |C_i - P_i| \right) \tag{1}$$

- "inaccuracy metric" (ρ)

$$\rho := \frac{\#\{i \in \{1, 2, \ldots, T\} \mid |C_i - P_i| > 2\}}{T}. \tag{2}$$





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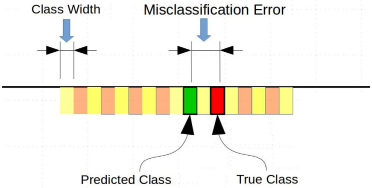

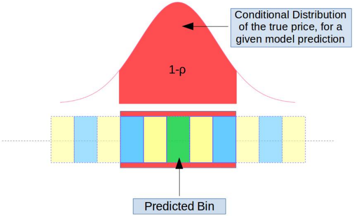

Input Vector or Feature Set

Composition of Feature Sets: An overview			
	Approach 1	*Approach 2*	*Approach 3*
Non Parametric Features	Order Statistics of the LR of the underlying asset	—	—
Parametric Features	—	Mean LR of OHLC Cov LR of OHLC	Mean LR of OHLC Cov LR of OHLC
Contract Features	Moneyness Time to Maturity	Moneyness Time to Maturity	Moneyness Time to Maturity Prev. Option Price (scaled) Mean Moneyness
Other	Interest Rate	Interest Rate	Interest Rate
Total	$19 + 3 = 22$ *features*	$4 + 10 + 3 = 17$ *features*	$4 + 10 + 5 = 19$ *features*

Table : An overview of feature sets for all the Approaches

Supervised Learning Algorithms

- Two algorithms: XGBoost and ANN
- The loss function - Categorical Cross Entropy.
- The weights are optimized using Adam optimiser, an advancement of the stochastic gradient descent optimizer.

Hyperparameter Name	**Value Set**
n_estimators	100
max_depth	3
learning_rate	0.3

Table : XGBoost

Hyperparameter Name	**Value Set**
batch_size	32
learning_rate	0.00012

Table : ANN

Composition of the ANN		
	Number of Neurons	*Activation Function*
Layer 1	128	ReLU
Layer 2	64	ReLU
Layer 3	50	softmax

Table : “Architecture” of the Neural Net used

Process Flowchart

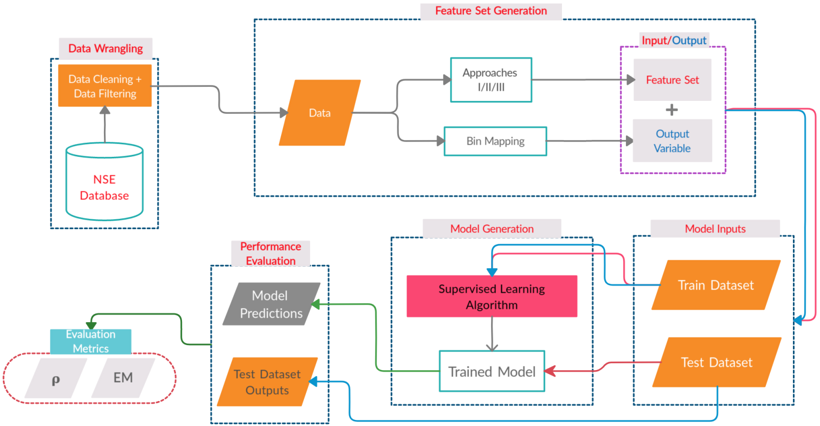

Figure : Process Flowchart

Out-Sample NIFTY50 Option Prediction

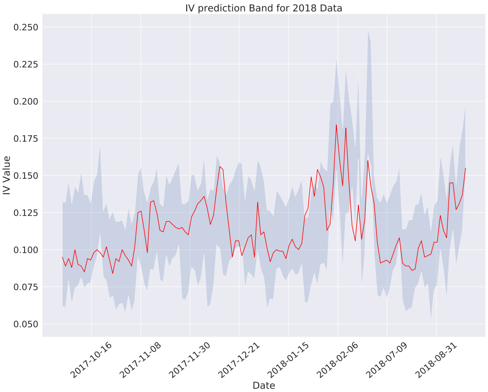

Figure : Average IV and the IV Band, plotted for the test dataset (2018 contracts) on NIFTY50 contracts using Approach III ANN

Ensemble Averaged models

The predictions of the two pricing models obtained using ANN and XGBoost for each approach can be averaged out, to obtain a new prediction.

Averaged Models :: NIFTY50		
	EM	ρ
Approach I	0.16	0.26
Approach II	0.16	0.27
Approach III	0.13	0.19

Table : Model evaluation metrics for ensemble averaged models trained and tested on NIFTY50 option contracts

B-S Pricing: $EM = 0.19$, $\rho = 0.29$

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Combined Training Model: Motivation

- Scale free I/O allows the model to give reasonable predictions when trained on another asset provided the log return distributions are not too different from each other.
- This allows the models to achieve far better generalization and predictive capability,
- Also solves the problem of paucity of data, the primary limitation of using machine learning techniques.

NIFTY50 models tested on BANKNIFTY				
	EM		ρ	
Trained Models	**ANN**	**XGB**	**ANN**	**XGB**
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Table : Model evaluation metrics for models trained on NIFTY50 contract data and tested on BANKNIFTY contracts

Combined Training Model: Motivation

- Scale free I/O allows the model to give reasonable predictions when trained on another asset provided the log return distributions are not too different from each other.
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Combined Training Model Error

Experiments using models trained on combined datasets								
	EM				ρ			
Test Dataset ::	**NIFTY50**		**BANKNIFTY**		**NIFTY50**		**BANKNIFTY**	
B-S Pricing	0.19		0.19		0.29		0.29	
Experiment Type	**ANN**	**XGB**	**ANN**	**XGB**	**ANN**	**XGB**	**ANN**	**XGB**
Approach I	0.17	0.17	0.18	0.19	0.24	0.24	0.25	0.25
Approach II	0.17	0.18	0.19	0.19	0.25	0.28	0.28	0.28
Approach III	0.14	0.16	0.16	0.17	0.17	0.22	0.23	0.23

Table : Model evaluation metrics for models trained on both NIFTY50 and BANKNIFTY option data

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Combined Training Model Prediction

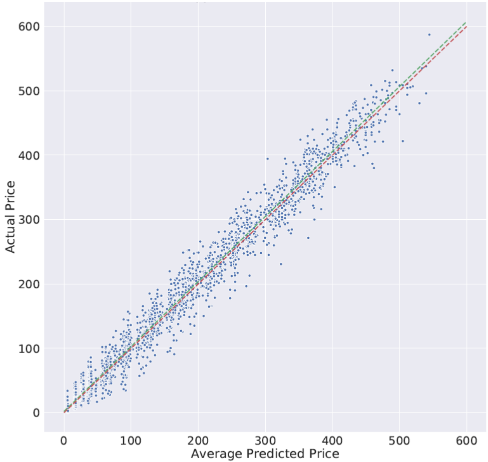

Figure : Actual vs 'Predicted' Price (obtained using Approach III based models trained on both NIFTY50 and BANKNIFTY contract data)

Empirical verification of arbitrage-free pricing

- In the scatter plot, Horizontal axis: Mid point of the bins, Vertical axis: Closed price from test data
- we add the identity line $y = x$ (red dashed line) and the orthogonal regression line (green dashed line).
- The proximity of these two lines cross-validates fair-pricing by the trained model.
- Indeed one can conduct tests of the hypothesis on the value of individual regression parameters. To be more precise, the intercept as zero and slope as 1.
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Challenge in Prediction on Covid-19 period Data

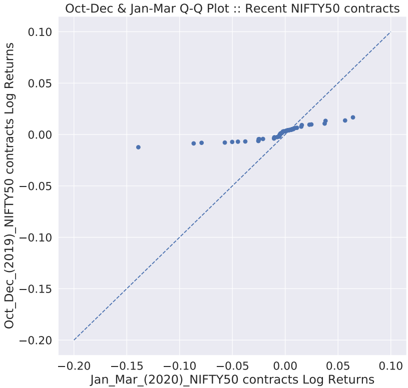

Figure : Q-Q plot of (Oct 2019 - Dec 2019) and (Jan 2020 - Mar 2020) datasets

Challenge in Prediction on Covid-19 period Data

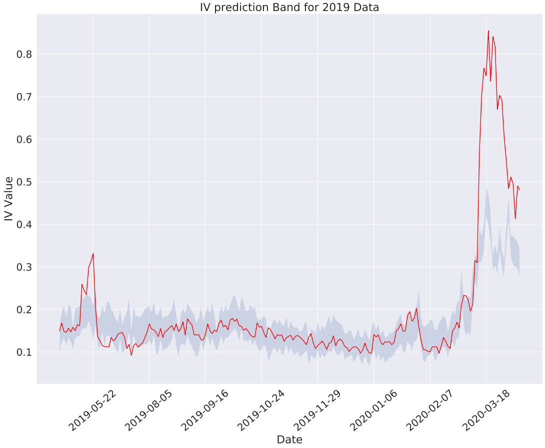

Figure : Average IV and the IV band for 2019 NIFTY50 index data

Introspection of Combined trained Models

1. Daily data is simulated from GBM for volatility parameters $1\% - 30\%$, BANKNIFTY and the combined data.
2. Test set that represents a trading session of 500 days.
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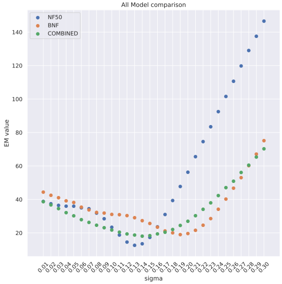

Figure : EM vs σ curve for ANN single- and combined- trained models in Approach I

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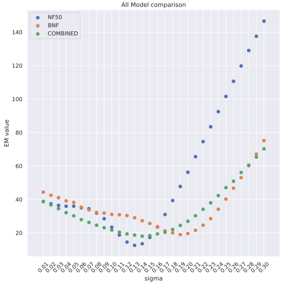

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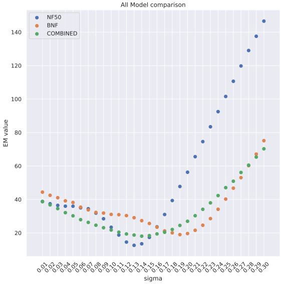

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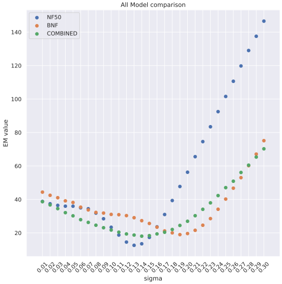

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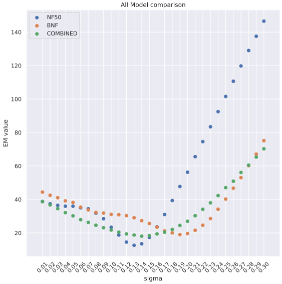

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Thank You