## **Task 1.A: Network Structure and Parameter Variation Analysis**

#### **Impact of Solver and Activation Function:**

- The L-BFGS solver with the Tanh activation function consistently achieved the highest training and testing accuracies, often reaching values very close to 1.0 (nearly perfect prediction).
- The SGD solver with the Identity activation function and inverse scaling learning rate performed poorly, often resulting in negative accuracies or errors.
- Choice of activation function had a significant impact on accuracy, with Tanh and ReLU generally outperforming the Identity function.

#### **Impact of Network Depth and Neurons:**

- Deeper networks with more hidden layers and neurons tended to perform better than shallower networks, but the improvement diminished after a certain depth.
- Increasing the number of hidden layers from 100 to (100, 50) generally improved prediction accuracy, especially when using the L-BFGS solver and the ReLU or Tanh activation functions.

# **Impact of Learning Rate Schemes:**

- The adaptive and inverse scaling learning rate schemes did not consistently improve performance compared to the constant learning rate.
- 'Constant' and 'invscaling' learning rate schedules generally performed better than the 'adaptive' schedule when using the Adam or L-BFGS solvers.

#### **Impact of Solver and Iterations:**

- The L-BFGS solver consistently produced higher prediction accuracies compared to the Adam and SGD solvers, especially when combined with the ReLU or Tanh activation functions and larger network structures.
- Increasing the maximum number of iterations from 500 to 1000 generally improved prediction accuracy, especially when using the L-BFGS or Adam solvers.

#### **Overall Recommendations:**

- Using deeper networks with appropriate activation functions (Tanh or ReLU), solvers like L-BFGS or Adam, and suitable learning rate schedules ('constant' or 'invscaling') can lead to higher prediction accuracies.
- Allowing for more training iterations (up to a certain point) seems to improve the model's performance.

Trial	Hidden	Activation	Learning	Solver	Max	Train	Test
Number	Layers		Rate		Iter	Accuracy	Accuracy
1	100	relu	constant	adam	500	0.9597	0.9616
2	100	relu	constant	adam	500	0.9669	0.9632
3	100	relu	constant	adam	500	0.9762	0.9719
1	100	relu	constant	adam	1000	0.9683	0.9609

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2	100	relu	constant	adam	1000	0.9713	0.9709
3	100	relu	constant	adam	1000	0.9667	0.9697
1	100	relu	adaptive	adam	500	0.9735	0.9681
2	100	relu	adaptive	adam	500	0.9755	0.9817
3	100	relu	adaptive	adam	500	0.9748	0.9696
1	100	relu	adaptive	adam	1000	0.9635	0.9569
2	100	relu	adaptive	adam	1000	0.9791	0.9765
3	100	relu	adaptive	adam	1000	0.946	0.9466
1	100	relu	invscaling	adam	500	0.9802	0.9809
2	100	relu	invscaling	adam	500	0.974	0.9755
3	100	relu	invscaling	adam	500	0.9526	0.9413
1	100	relu	invscaling	adam	1000	0.9776	0.9817
2	100	relu	invscaling	adam	1000	0.9786	0.9729
3	100	relu	invscaling	adam	1000	0.9714	0.9644
1	100	relu	constant	lbfgs	500	0.9895	0.9868
1	100	relu	constant	adam	500	0.988	0.9851
2	100	relu	constant	adam	500	0.9888	0.9905
1	100	relu	constant	adam	1000	0.993	0.9897
2	100	relu	constant	adam	1000	0.9954	0.9947
3	100	relu	constant	adam	1000	0.9922	0.9924
1	100	relu	adaptive	adam	500	0.9939	0.9954
2	100	relu	adaptive	adam	500	0.9915	0.9925
3	100	relu	adaptive	adam	500	0.9875	0.9922
1	100	relu	adaptive	adam	1000	0.995	0.994
2	100	relu	adaptive	adam	1000	0.9955	0.9956
3	100	relu	adaptive	adam	1000	0.9939	0.9935
1	100	relu	invscaling	adam	500	0.9896	0.9907
2	100	relu	invscaling	adam	500	0.9851	0.9873
3	100	relu	invscaling	adam	500	0.9886	0.9906
1	100	relu	invscaling	adam	1000	0.996	0.9946
2	100	relu	invscaling	adam	1000	0.9933	0.9974
3	100	relu	invscaling	adam	1000	0.9925	0.9936
1	100	relu	constant	lbfgs	500	0.9073	0.9122
2	100	relu	constant	lbfgs	500	0.9161	0.9093
1	100	relu	constant	adam	500	0.988	0.9851
2	100	relu	constant	adam	500	0.9888	0.9905
1	100	relu	constant	adam	1000	0.993	0.9897
2	100	relu	constant	adam	1000	0.9954	0.9947
3	100	relu	constant	adam	1000	0.9922	0.9924
1	100	relu	adaptive	adam	500	0.9939	0.9954
2	100	relu	adaptive	adam	500	0.9915	0.9925
3	100	relu	adaptive	adam	500	0.9875	0.9922
1	100	relu	adaptive	adam	1000	0.995	0.994
2	100	relu	adaptive	adam	1000	0.9955	0.9956

3	100	relu	adaptive	adam	1000	0.9939	0.9935
1	100	relu	invscaling	adam	500	0.9896	0.9907
2	100	relu	invscaling	adam	500	0.9851	0.9873
3	100	relu		adam	500	0.9886	0.9973
1	100		invscaling		1000	0.986	0.9946
		relu	invscaling	adam			
2	100	relu	invscaling	adam	1000	0.9933	0.9974
3	100	relu	invscaling	adam	1000	0.9925	0.9936
1	100	relu	constant	lbfgs	500	0.9073	0.9122
2	100	relu	constant	lbfgs	500	0.9161	0.9093
3	100	relu	constant	sgd	500	0.9191	0.9074
1	100	relu	constant	sgd	1000	0.9215	0.9169
2	100	relu	constant	sgd	1000	0.9128	0.9326
3	100	relu	constant	sgd	1000	0.9123	0.9143
1	100	relu	adaptive	sgd	500	0.9159	0.9164
2	100	relu	adaptive	sgd	500	0.9045	0.891
3	100	relu	adaptive	sgd	500	0.9053	0.8899
1	100	relu	adaptive	sgd	1000	0.9312	0.921
2	100	relu	adaptive	sgd	1000	0.8935	0.8785
3	100	relu	adaptive	sgd	1000	0.9229	0.9302
1	100	relu	invscaling	sgd	500	-0.1315	-0.0488
2	100	relu	invscaling	sgd	500	-0.2105	-0.3848
3	100	relu	invscaling	sgd	500	-0.1108	-0.3193
1	100	relu	invscaling	sgd	1000	-0.3024	-0.296
2	100	relu	invscaling	sgd	1000	-0.3244	-0.3631
3	100	relu	invscaling	sgd	1000	-0.2825	-0.311
1	100	identity	constant	adam	500	0.6835	0.7045
2	100	identity	constant	adam	500	0.6931	0.7157
3	100	identity	constant	adam	500	0.6897	0.6641
1	100	identity	constant	adam	1000	0.6991	0.7088
2	100	identity	constant	adam	1000	0.6913	0.6718
3	100	identity	constant	adam	1000	0.6961	0.7036
1	100	tanh	invscaling	adam	1000	0.9669	0.9627
2	100	tanh	invscaling	adam	1000	0.9644	0.9554
3	100	tanh	invscaling	adam	1000	0.9683	0.9616
1	100	tanh	constant	lbfgs	500	0.9858	0.9909
2	100	tanh	constant	lbfgs	500	0.988	0.9842
3	100	tanh	constant	lbfgs	500	0.9861	0.9877
1	100	tanh	constant	lbfgs	1000	0.9887	0.991
2	100	tanh	constant	lbfgs	1000	0.9911	0.9929
3	100	tanh	constant	lbfgs	1000	0.9883	0.9879
1	100	tanh	adaptive	lbfgs	500	0.9876	0.9859
2	100	tanh	adaptive	lbfgs	500	0.9889	0.9811
3	100	tanh	adaptive	lbfgs	500	0.986	0.9825
1	100	tanh	adaptive	lbfgs	1000	0.9882	0.9918

2	100	tanh	adaptive	lbfgs	1000	0.9907	0.9903
3	100	tanh	adaptive	lbfgs	1000	0.9904	0.9919
1	100	tanh	invscaling	lbfgs	500	0.9868	0.9866
2	100	tanh	invscaling	lbfgs	500	0.9888	0.9826
3	100	tanh	invscaling	lbfgs	500	0.9873	0.9806
1	100	tanh	invscaling	lbfgs	1000	0.9895	0.9854
2	100	tanh	invscaling	lbfgs	1000	0.9898	0.9836
3	100	tanh	invscaling	lbfgs	1000	0.9878	0.9868
1	100	tanh	constant	sgd	500	0.947	0.9459
2	100	tanh	constant	sgd	500	0.9436	0.9374
3	100	tanh	constant	sgd	500	0.9406	0.9437
1	100	tanh	constant	sgd	1000	0.9448	0.9507
2	100	tanh	constant	sgd	1000	0.9391	0.95
3	100	tanh	constant	sgd	1000	0.9463	0.9544
1	100	tanh	adaptive	sgd	500	0.9475	0.9602
2	100	tanh	adaptive	sgd	500	0.9484	0.9483
3	100	tanh	adaptive	sgd	500	0.9472	0.9403
1	100	tanh	adaptive	sgd	1000	0.9414	0.9318
2	100	tanh	adaptive	sgd	1000	0.9487	0.9419
3	100	tanh	adaptive	sgd	1000	0.9452	0.9466
1	100	tanh	invscaling	sgd	500	0.1178	0.047
2	100	tanh	invscaling	sgd	500	-0.1047	0.0131
3	100	tanh	invscaling	sgd	500	0.2068	0.1667
1	100	tanh	invscaling	sgd	1000	0.1064	-0.0166
2	100	tanh	invscaling	sgd	1000	0.2814	0.3544
3	100	tanh	invscaling	sgd	1000	-0.0265	-0.0973
1	(100,	relu	constant	adam	500	0.9838	0.9778
	50)						
2	(100,	relu	constant	adam	500	0.9898	0.988
0	50)				500	0.075	0.0005
3	(100, 50)	relu	constant	adam	500	0.975	0.9685
1	(100,	relu	constant	adam	1000	0.984	0.9865
'	50)	Tota	Conocant	adam	1000	0.004	0.0000
2	(100,	relu	constant	adam	1000	0.9778	0.9771
	50)						
3	(100,	relu	constant	adam	1000	0.9879	0.988
	50)					0.000	0.0700
3	(100,	relu	invscaling	adam	500	0.9808	0.9706
1	50) (100,	relu	invscaling	adam	1000	0.9863	0.9876
'	50)	1014	invocating	addill	1000	0.000	0.0070
2	(100,	relu	invscaling	adam	1000	0.9879	0.9896
	50)						
3	(100,	relu	invscaling	adam	1000	0.9776	0.9803
	50)						

1	(100,	relu	constant	lbfgs	500	0.9928	0.9928
	50)	. 515	00110101111	13.85		0.0020	0.0020
2	(100,	relu	constant	lbfgs	500	0.9915	0.9949
	50)						
3	(100, 50)	relu	constant	lbfgs	500	0.9913	0.9916
1	(100,	relu	constant	lbfgs	1000	0.9963	0.9923
	50)	Tota	Constant	15155	1000	0.0000	0.0020
2	(100,	relu	constant	lbfgs	1000	0.9954	0.9979
	50)						
3	(100,	relu	constant	lbfgs	1000	0.9972	0.9951
1	50)	relu	adaptive	lbfgs	500	0.9952	0.9964
'	50)	Tota	adaptive	tbigs	300	0.5552	0.5504
2	(100,	relu	adaptive	lbfgs	500	0.994	0.9903
	50)						
3	(100,	relu	adaptive	lbfgs	500	0.9926	0.9763
	50)			11.6	1000	0.0000	2 2222
1	(100, 50)	relu	adaptive	lbfgs	1000	0.9963	0.9888
2	(100,	relu	adaptive	lbfgs	1000	0.991	0.9952
_	50)	Tota	adaptivo	tolgo	1000	0.001	0.0002
3	(100,	relu	adaptive	lbfgs	1000	0.9967	0.9919
	50)						
1	(100,	relu	invscaling	lbfgs	500	0.9945	0.9883
	50)			11-4	500	0.0050	0.0000
2	(100, 50)	relu	invscaling	lbfgs	500	0.9952	0.9886
3	(100,	relu	invscaling	lbfgs	500	0.9933	0.9848
	50)		8				
1	(100,	relu	invscaling	lbfgs	1000	0.9963	0.9888
	50)						
2	(100,	relu	invscaling	lbfgs	1000	0.9962	0.998
3	50)	relu	invscaling	lbfgs	1000	0.9956	0.9964
3	50)	Tetu	invocating	tuigs	1000	0.9950	0.9904
1	(100,	relu	constant	sgd	500	0.9336	0.9478
	50)			J			
2	(100,	relu	constant	sgd	500	0.9156	0.9186
	50)				500	0.0556	0.07.16
3	(100, 50)	relu	constant	sgd	500	0.9559	0.9543
1	(100,	relu	constant	sgd	1000	0.9513	0.9541
'	50)	1014	Jonatant	- 05u	1000	0.0010	0.0041
2	(100,	relu	constant	sgd	1000	0.9334	0.9279
	50)			-			
3	(100,	relu	constant	sgd	1000	0.9415	0.9302
1	50)	mals:	a al c :- #:	I	500	0.0400	0.0407
1	(100,	relu	adaptive	sgd	500	0.9483	0.9407
	50)	<u> </u>	<u> </u>		]	<u> </u>	

2	(100,	relu	adaptive	sgd	500	0.9496	0.9462
	50)						
3	(100, 50)	relu	adaptive	sgd	500	0.9613	0.9567
1	(100, 50)	relu	adaptive	sgd	1000	0.9527	0.9461
2	(100, 50)	relu	adaptive	sgd	1000	0.9554	0.9627
3	(100, 50)	relu	adaptive	sgd	1000	0.9453	0.938
1	(100, 50)	relu	invscaling	sgd	500	0.0727	-0.1096
2	(100, 50)	relu	invscaling	sgd	500	-0.0404	-0.0765
3	(100, 50)	relu	invscaling	sgd	500	-0.3171	-0.3162
1	(100, 50)	relu	invscaling	sgd	1000	-0.2701	-0.2953
2	(100, 50)	relu	invscaling	sgd	1000	-0.2047	-0.601
3	(100, 50)	relu	invscaling	sgd	1000	-0.2087	-0.0831
1	(100, 50)	identity	constant	adam	500	0.6801	0.6891
2	(100, 50)	identity	constant	adam	500	0.6983	0.6908
3	(100, 50)	identity	constant	adam	500	0.6922	0.6907
1	(100, 50)	identity	constant	adam	1000	0.6882	0.6783
2	(100, 50)	identity	constant	adam	1000	0.7026	0.6865
3	(100, 50)	identity	constant	adam	1000	0.6953	0.6856
3	(100, 50)	tanh	invscaling	adam	500	0.9727	0.9807
1	(100, 50)	tanh	invscaling	adam	1000	0.9816	0.9809
2	(100, 50)	tanh	invscaling	adam	1000	0.9828	0.9874
3	(100, 50)	tanh	invscaling	adam	1000	0.9805	0.9781
1	(100, 50)	tanh	constant	lbfgs	500	0.9937	0.9965
2	(100, 50)	tanh	constant	lbfgs	500	0.9952	0.9949
3	(100, 50)	tanh	constant	lbfgs	500	0.9941	0.9907
1	(100, 50)	tanh	constant	lbfgs	1000	0.9965	0.9956

2	(100,	tanh	constant	lbfgs	1000	0.9975	0.996
3	50) (100,	tanh	constant	lbfgs	1000	0.9967	0.9983
	50)						
1	(100, 50)	tanh	adaptive	lbfgs	500	0.995	0.9924
2	(100, 50)	tanh	adaptive	lbfgs	500	0.9952	0.9943
3	(100, 50)	tanh	adaptive	lbfgs	500	0.9957	0.9979
1	(100, 50)	tanh	adaptive	lbfgs	1000	0.9965	0.9976
2	(100, 50)	tanh	adaptive	lbfgs	1000	0.9968	0.9928
3	(100, 50)	tanh	adaptive	lbfgs	1000	0.9982	0.999
1	(100, 50)	tanh	invscaling	lbfgs	500	0.9944	0.9919
2	(100, 50)	tanh	invscaling	lbfgs	500	0.9943	0.997
3	(100, 50)	tanh	invscaling	lbfgs	500	0.9956	0.9954
1	(100, 50)	tanh	invscaling	lbfgs	1000	0.9978	0.9975
2	(100, 50)	tanh	invscaling	lbfgs	1000	0.9971	0.9915
3	(100, 50)	tanh	invscaling	lbfgs	1000	0.998	0.9991
1	(100, 50)	tanh	constant	sgd	500	0.9515	0.9454
2	(100, 50)	tanh	constant	sgd	500	0.9562	0.9458
3	(100, 50)	tanh	constant	sgd	500	0.9507	0.9488
1	(100, 50)	tanh	constant	sgd	1000	0.9564	0.9573
2	(100, 50)	tanh	constant	sgd	1000	0.9559	0.9609
3	(100, 50)	tanh	constant	sgd	1000	0.9531	0.9683
1	(100, 50)	tanh	adaptive	sgd	500	0.9563	0.955
2	(100, 50)	tanh	adaptive	sgd	500	0.9605	0.9597
3	(100, 50)	tanh	adaptive	sgd	500	0.9523	0.955
1	(100, 50)	tanh	adaptive	sgd	1000	0.9455	0.9565
2	(100, 50)	tanh	adaptive	sgd	1000	0.9466	0.9494

3	(100, 50)	tanh	adaptive	sgd	1000	0.9554	0.9592
1	(100, 50)	tanh	invscaling	sgd	500	0.3914	0.3809
2	(100, 50)	tanh	invscaling	sgd	500	0.2305	0.2803
3	(100, 50)	tanh	invscaling	sgd	500	0.2511	0.3048
1	(100, 50)	tanh	invscaling	sgd	1000	-0.7925	-0.8919
2	(100, 50)	tanh	invscaling	sgd	1000	0.3944	0.3636
3	(100, 50)	tanh	invscaling	sgd	1000	0.2452	0.3621

## Task 1.B: Quantity of Training Data and Joint Range Impact Analysis

## **Impact of Training Data Quantity:**

- Increasing the number of training samples from 1000 to 2000 and 5000 generally led to improved accuracies for both training and testing datasets.
- However, the improvement exhibited diminishing returns, indicating that beyond a certain threshold, adding more training data did not significantly boost accuracy.

# **Impact of Joint Ranges:**

- Joint range combinations that included the full range (0, 3.142) for either joint consistently achieved higher accuracies compared to limited range combinations (-0.785, 1.571) or (-1.571, 1.571).
- The highest accuracies were observed when both joint ranges were set to the full range (0, 3.142), highlighting the importance of broader joint ranges for better generalization and prediction performance.
- Wider joint ranges fostered higher accuracies, emphasizing the significance of training data diversity in enhancing the model's generalization capability.

#### **Interaction between Training Data Quantity and Joint Ranges:**

- Increasing training data size had a more significant positive impact on accuracy for joint range combinations including the full range (0, 3.142) compared to limited range combinations.
- This suggests that when joint ranges are broader, providing more training data helps the model better capture underlying patterns and improve prediction capability.

# **Observations and Recommendations (Aligned with Previous Report):**

 The Tanh activation function consistently outperformed ReLU and Identity due to its nonlinearity and smoothness, making it suitable for modelling complex inverse kinematics mapping.

- The L-BFGS solver achieved the highest accuracies, being effective at optimizing nonconvex problems like inverse kinematics.
- Constant or adaptive learning rate schemes were preferable, while the inverse scaling learning rate often led to poor performance or instabilities.
- A deep network architecture with 7 hidden layers and a wide range of neurons proved sufficient for capturing the problem's complexities.
- The provided dataset size of 1800 training samples and 200 test samples was adequate for achieving high accuracies, indicating its representativeness and diversity.

# **Recommended Configuration:**

- Combination of Tanh activation function, L-BFGS solver, and constant or adaptive learning rate scheme.
- Deep network architecture with (500, 400, 300, 200, 100, 50, 25) neurons in hidden layers.

• Maximum iterations: 2000.

• Training set size: 1800 samples.

• Test set size: 200 samples.

Training	Test	Joint 1	Joint 2	Train	Test
Samples	Samples	Range	Range	Accuracy	Accuracy
1000	200	(-0.785,	(-0.785,	0.805	0.7927
		1.571)	1.571)		
1000	200	(-0.785,	(-1.571,	0.6145	0.5654
		1.571)	1.571)		
1000	200	(-0.785,	(0,	0.9777	0.9722
		1.571)	3.142)		
1000	200	(-1.571,	(-0.785,	0.7369	0.6475
		1.571)	1.571)		
1000	200	(-1.571,	(-1.571,	0.5434	0.5289
		1.571)	1.571)		
1000	200	(-1.571,	(0,	0.9897	0.9839
		1.571)	3.142)		
1000	200	(0,	(-0.785,	0.7863	0.7665
		3.142)	1.571)		
1000	200	(0,	(-1.571,	0.5508	0.4974
		3.142)	1.571)		
1000	200	(0,	(0,	0.9814	0.9757
		3.142)	3.142)		
1000	500	(-0.785,	(-0.785,	0.79	0.7987
		1.571)	1.571)		
1000	500	(-0.785,	(-1.571,	0.5183	0.479
		1.571)	1.571)		

1000	500	(-0.785,	(0,	0.968	0.9675
		1.571)	3.142)		
1000	500	(-1.571,	(-0.785,	0.8095	0.7921
		1.571)	1.571)		
1000	500	(-1.571,	(-1.571,	0.5366	0.522
		1.571)	1.571)		
1000	500	(-1.571,	(0,	0.9823	0.9817
		1.571)	3.142)		
1000	500	(0,	(-0.785,	0.8228	0.7999
		3.142)	1.571)		
1000	500	(0,	(-1.571,	0.5861	0.5567
1000	F00	3.142)	1.571)	0.0000	0.0770
1000	500	(0, 3.142)	(0, 3.142)	0.9838	0.9778
1000	1000	(-0.785,	(-0.785,	0.8085	0.8034
1000	1000	1.571)	1.571)	0.0003	0.8034
1000	1000	(-0.785,	(-1.571,	0.5043	0.5197
1000	1000	1.571)	1.571)	0.5045	0.5157
1000	1000	(-0.785,	(0,	0.9853	0.9821
1000	1000	1.571)	3.142)	0.0000	0.0021
1000	1000	(-1.571,	(-0.785,	0.8062	0.7879
		1.571)	1.571)	0.000	
1000	1000	(-1.571,	(-1.571,	0.5317	0.5133
		1.571)	1.571)		
1000	1000	(-1.571,	(0,	0.9763	0.9764
		1.571)	3.142)		
1000	1000	(0,	(-0.785,	0.8162	0.7907
		3.142)	1.571)		
1000	1000	(0,	(-1.571,	0.5791	0.558
		3.142)	1.571)		
1000	1000	(0,	(0,	0.9768	0.9767
		3.142)	3.142)		
2000	200	(-0.785,	(-0.785,	0.8037	0.7914
		1.571)	1.571)		
2000	200	(-0.785,	(-1.571,	0.585	0.5558
		1.571)	1.571)		
2000	200	(-0.785,	(0,	0.9903	0.9881
		1.571)	3.142)		
2000	200	(-1.571,	(-0.785,	0.8021	0.8246
0000	000	1.571)	1.571)	0.5704	0.5455
2000	200	(-1.571,	(-1.571,	0.5794	0.5455
2000	200	1.571)	1.571)	0.0017	0.0000
2000	200	(-1.571,	(0,	0.9917	0.9939
2000	200	1.571)	3.142)	0 0111	0.00E4
2000	200	(0, 3.142)	(-0.785, 1.571)	0.8111	0.8054
2000	200			0.5568	0.5057
2000	200	(0, 3.142)	(-1.571, 1.571)	0.5566	0.5057
	L	J. 142)	1.371)		

2000	200	(0,	(0,	0.9901	0.9875
		3.142)	3.142)		
2000	500	(-0.785,	(-0.785,	0.8119	0.8022
		1.571)	1.571)		
2000	500	(-0.785,	(-1.571,	0.6218	0.6
		1.571)	1.571)		
2000	500	(-0.785,	(0,	0.99	0.9903
		1.571)	3.142)		
2000	500	(-1.571,	(-0.785,	0.8199	0.8212
2000	300	1.571)	1.571)	0.0133	0.0212
2000	500		(-1.571,	0.5891	0.5542
2000	500	(-1.571, 1.571)	1.571)	0.5691	0.5542
2000	500		,	0.0070	0.0005
2000	500	(-1.571,	(0,	0.9878	0.9825
		1.571)	3.142)		
2000	500	(0,	(-0.785,	0.8126	0.8133
		3.142)	1.571)		
2000	500	(0,	(-1.571,	0.5975	0.5885
		3.142)	1.571)		
2000	500	(0,	(0,	0.9902	0.9871
		3.142)	3.142)		
2000	1000	(-0.785,	(-0.785,	0.7933	0.8024
		1.571)	1.571)		
2000	1000	(-0.785,	(-1.571,	0.6231	0.6023
2000	1000	1.571)	1.571)	0.0201	0.0020
2000	1000	(-0.785,	(0,	0.989	0.9897
2000	1000	1.571)	3.142)	0.909	0.9697
2000	1000	,	,	0.0000	0.7000
2000	1000	(-1.571,	(-0.785,	0.8096	0.7906
		1.571)	1.571)		
2000	1000	(-1.571,	(-1.571,	0.5939	0.5944
		1.571)	1.571)		
2000	1000	(-1.571,	(0,	0.9828	0.9807
		1.571)	3.142)		
2000	1000	(0,	(-0.785,	0.8213	0.796
		3.142)	1.571)		
2000	1000	(0,	(-1.571,	0.5085	0.5168
		3.142)	1.571)		
2000	1000	(0,	(0,	0.9825	0.9825
		3.142)	3.142)		
5000	200	(-0.785,	(-0.785,	0.7926	0.8342
		1.571)	1.571)		
5000	200	(-0.785,	(-1.571,	0.6172	0.6336
	200	1.571)	1.571)	0.01/2	
5000	200	_	•	0.9944	0.9933
3000	200	(-0.785,	(0, 3.142)	0.5544	0.5500
5000	000	1.571)		0.0050	0.0004
5000	200	(-1.571,	(-0.785,	0.8259	0.8091
		1.571)	1.571)		
5000	200	(-1.571,	(-1.571,	0.5939	0.5794
]		1.571)	1.571)		

5000	200	(-1.571,	(0,	0.9947	0.9968
		1.571)	3.142)		
5000	200	(0,	(-0.785,	0.8126	0.8395
		3.142)	1.571)		
5000	200	(0,	(-1.571,	0.5905	0.5778
		3.142)	1.571)		
5000	200	(0,	(0,	0.9931	0.9913
		3.142)	3.142)		
5000	500	(-0.785,	(-0.785,	0.8126	0.7814
		1.571)	1.571)		
5000	500	(-0.785,	(-1.571,	0.6218	0.5968
		1.571)	1.571)		
5000	500	(-0.785,	(0,	0.9933	0.9935
		1.571)	3.142)		
5000	500	(-1.571,		0.8179	0.8257
		1.571)	1.571)		
5000	500	(-1.571,	(-1.571,	0.589	0.5667
		1.571)	1.571)		
5000	500	(-1.571,	(0,	0.9921	0.9921
		1.571)	3.142)		
5000	500	(0,	(-0.785,	0.8011	0.7877
		3.142)	1.571)		
5000	500	(0,	(-1.571,	0.5949	0.5928
		3.142)	1.571)		
5000	500	(0,	(0,	0.9944	0.9925
		3.142)	3.142)		
5000	1000	(-0.785,	(-0.785,	0.8101	0.7891
		1.571)	1.571)		
5000	1000	(-0.785,	(-1.571,	0.6091	0.6043
5000	4000	1.571)	1.571)	0.0044	0.0040
5000	1000	(-0.785,	(0,	0.9941	0.9946
		1.571)	3.142)		
5000	1000	(-1.571,	(-0.785,	0.8079	0.7984
5000	4000	1.571)	1.571)	0.5004	0.5050
5000	1000	(-1.571,	(-1.571,	0.5994	0.5856
5000	4000	1.571)	1.571)	2 2225	0.0000
5000	1000	(-1.571,	(0,	0.9935	0.9939
5000	4000	1.571)	3.142)	0.0000	0.000=
5000	1000	(0,	(-0.785,	0.8228	0.8067
5000	4000	3.142)	1.571)	0.5040	0.5764
5000	1000	(0,	(-1.571,	0.5912	0.5791
5000		3.142)	1.571)	0.0001	0.0040
1 COO			1 (1)		0.0040
5000	1000	(0, 3.142)	(0, 3.142)	0.9934	0.9919