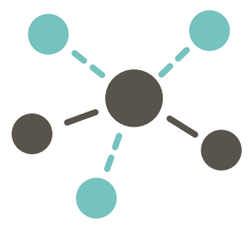
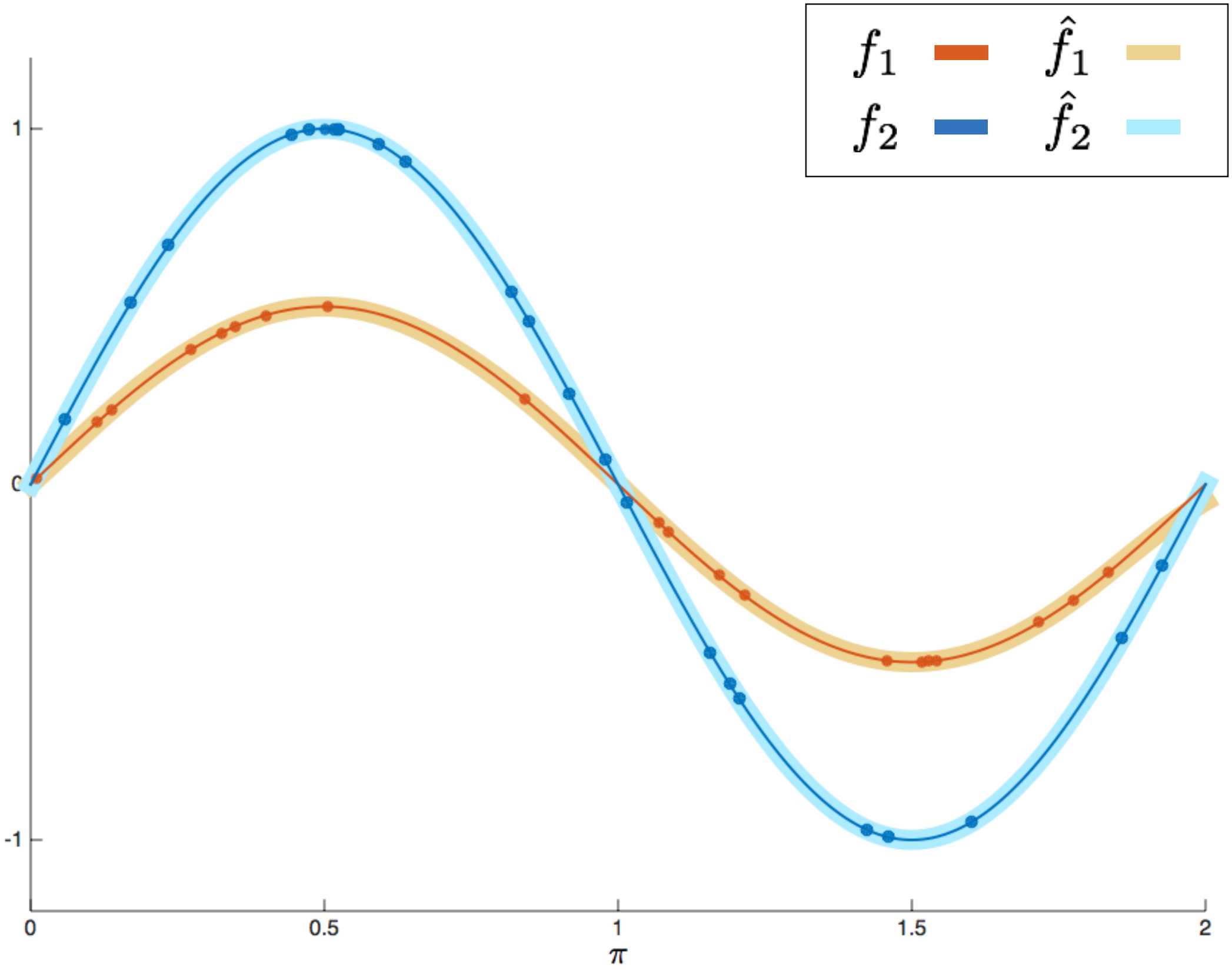
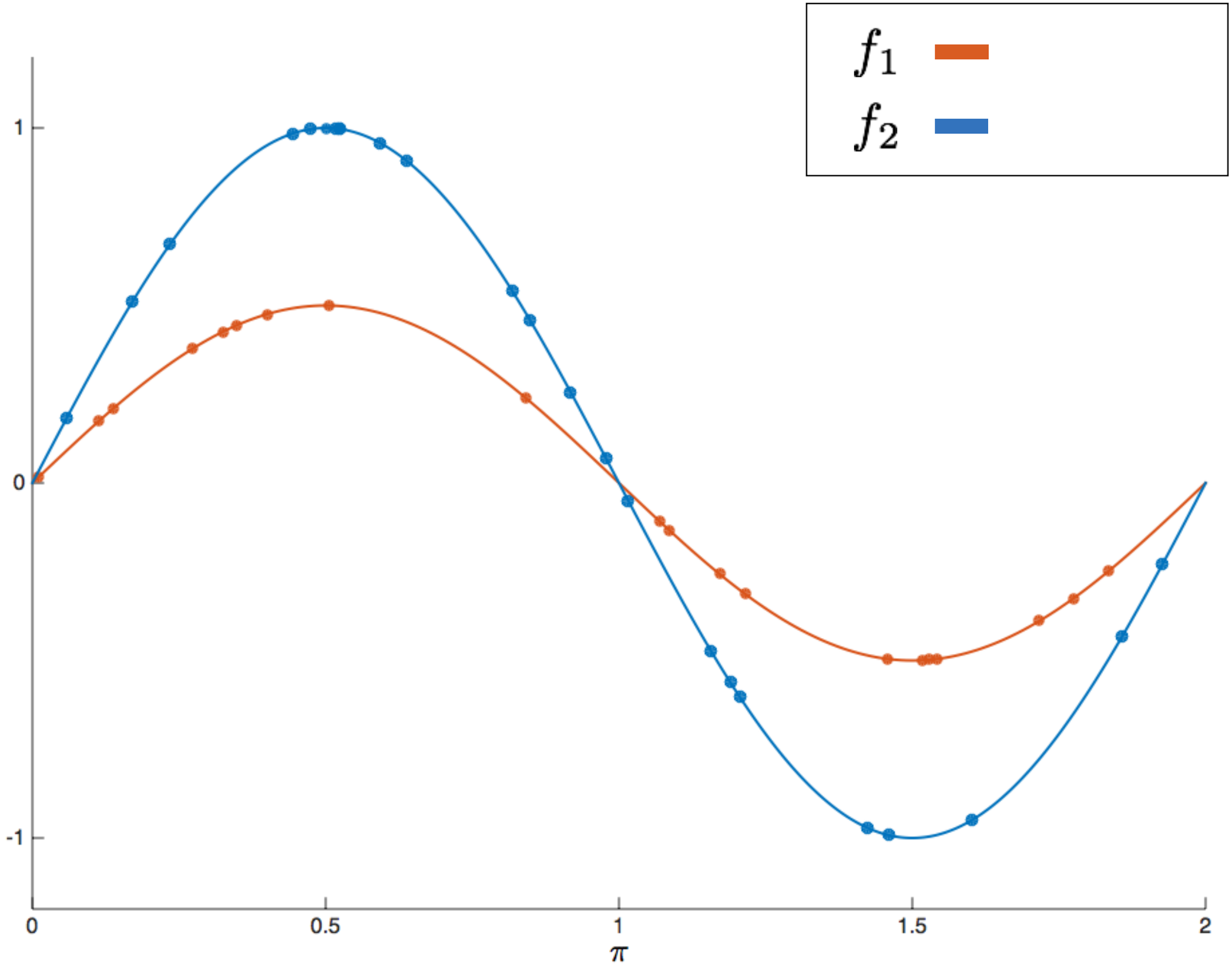
A Unifying Framework for Multi-task Learning



Carlo Ciliberto


f_1
$\hat{f}_1$
f_2
$\hat{f}_2$
1
0
-1
0
0.5
1
1.5
2
π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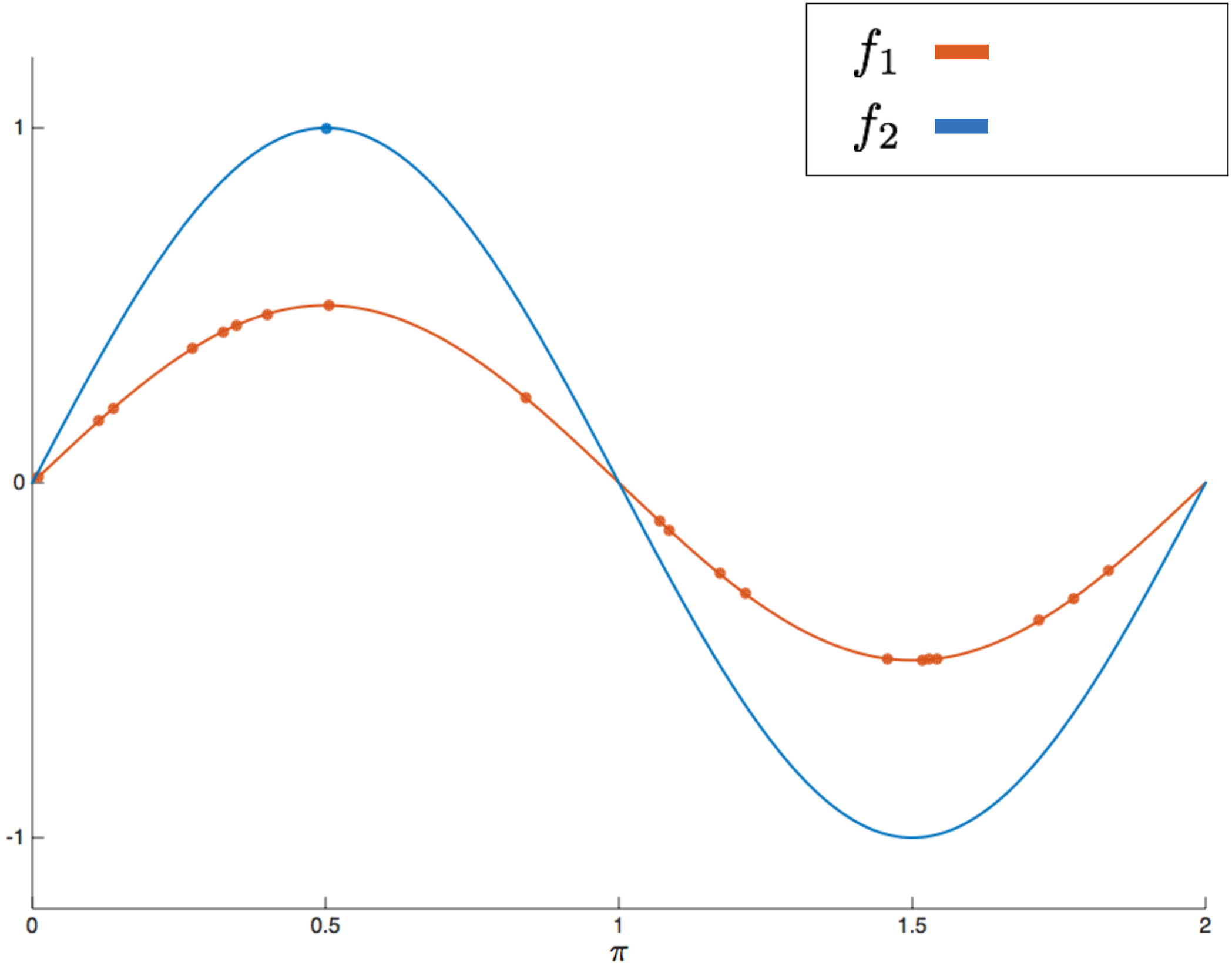
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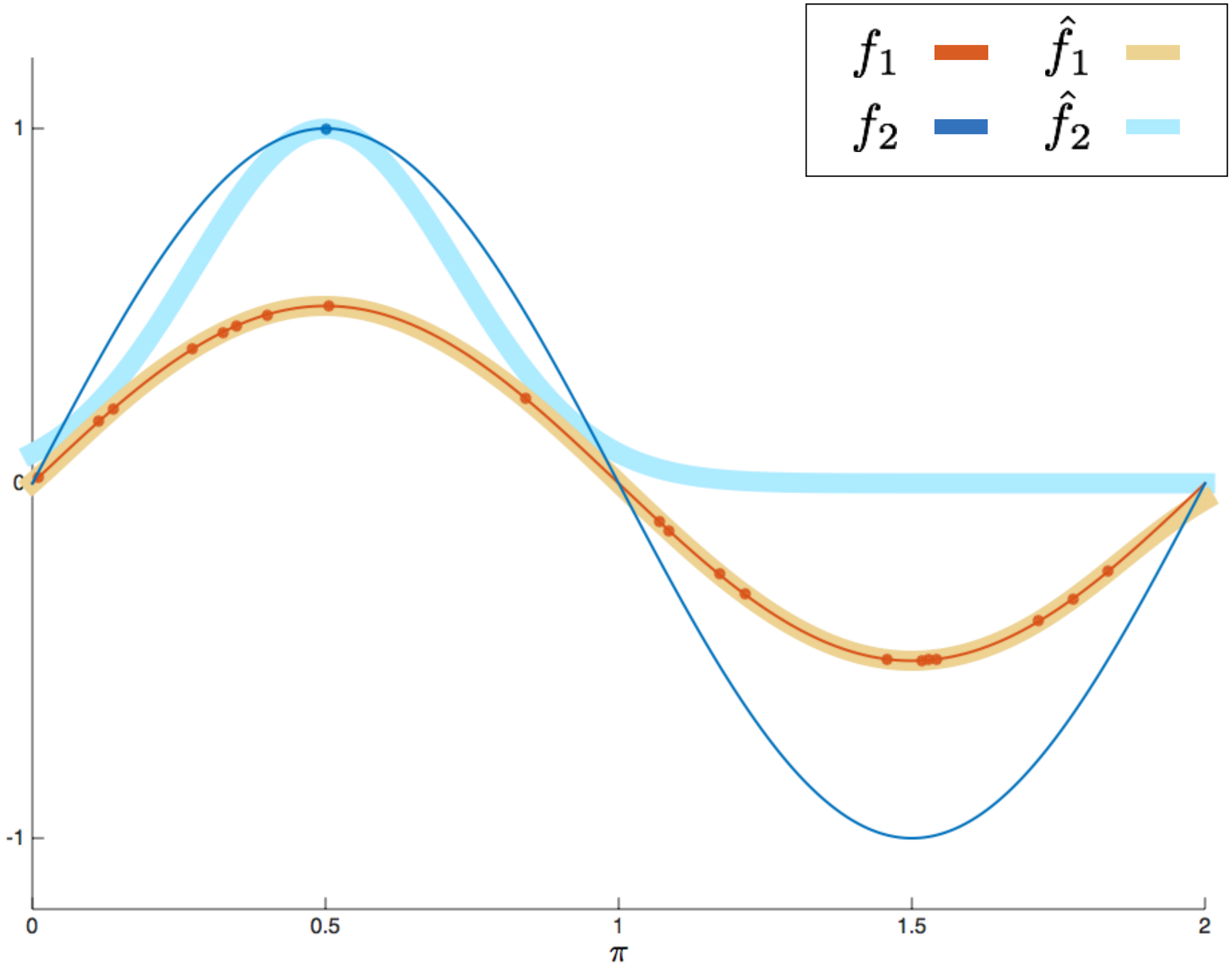
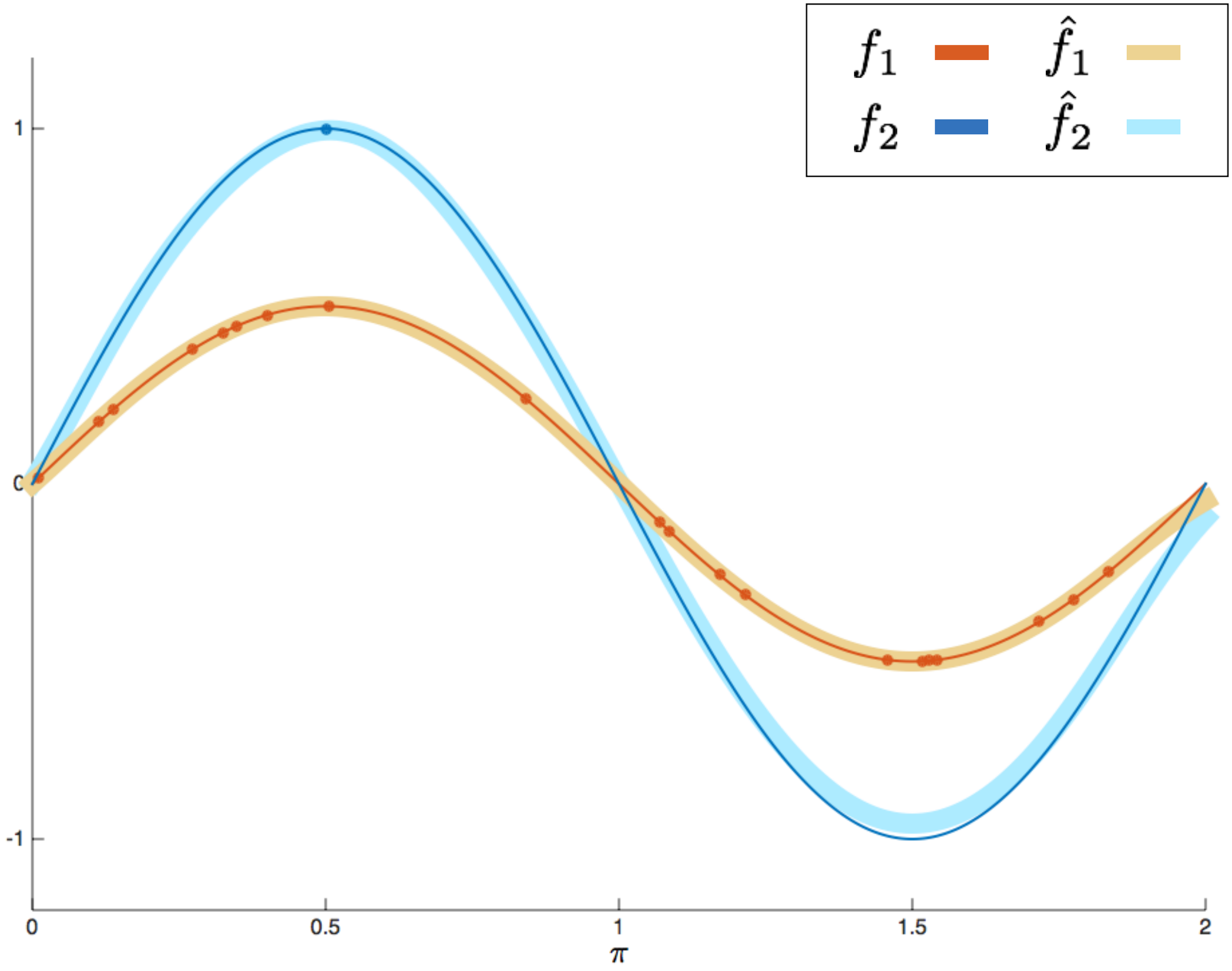


Without Sharing Information



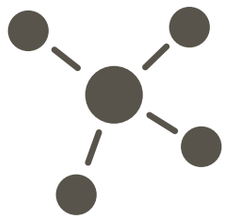
Sharing Information

Multi-task Learning: Assumption

Leveraging on the tasks relations/structure reduces the complexity of the problem

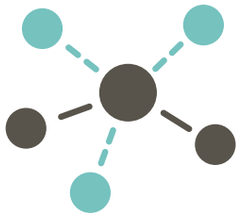
$$
\begin{aligned}
n12 &\to +\infty \\
n17 &\to +\infty \\
n22 &\to +\infty \\
n27 &\to +\infty \\
n32 &\to +\infty \\
n37 &\to +\infty \\
n42 &\to +\infty \\
47 &\to +\infty \\
2 &\to +\infty \\
&\to +\infty \\
&\to +\infty \\
&\to +\infty \\
&\to +\infty \\
&\to +\infty \\
&\to +\infty \\
&\to +\infty \\
&\to +\infty
\end{aligned}
\qquad
\begin{aligned}
n28 &\to +\infty \\
n33 &\to +\infty \\
n38 &\to +\infty \\
n43 &\to +\infty \\
n48 &\to +\infty \\
n53 &\to +\infty \\
n58 &\to +\infty \\
n63 &\to +\infty \\
n68 &\to +\infty \\
n73 &\to +\infty \\
n78 &\to +\infty \\
n83 &\to +\infty \\
n88 &\to +\infty \\
n93 &\to +\infty \\
n98 &\to +\infty
\end{aligned}
\qquad
\begin{aligned}
n39 &\to +\infty \\
n44 &\to +\infty \\
n49 &\to +\infty \\
n54 &\to +\infty \\
n59 &\to +\infty \\
n64 &\to +\infty \\
n69 &\to +\infty \\
n7 &\to +\infty \\
n &\to +\infty \\
&\to +\infty \\
&\to +\infty \\
&\to +\infty \\
&\to +\infty \\
&\to +\infty \\
&\to +\infty \\
&\to +\infty
\end{aligned}
$$

$$n_{T+1} \to 1$$



Impose known structures

[Evgeniou et al. 2005, Fergus et al. 2010, Kadri et al. 2010, Minh et al 2013, Jayaraman et al., 2014 and many others]



Parametrize and Learn the structure

[Argyriou et al. 2008, Jacob et al. 2009, Zhang et al, 2010 Dinuzzo et al. 2011, Zhong 2012, and many other]

Conjoint Analysis

Transfer Learning

Learning To Learn

Embeddings

Task-relations Learning

Cluster-Task Learning

Structured Output Learning

Multi-Task Learning

Matrix-valued Kernel Learning

Output Covariance Learning

Metric Deformation

Output Representation Learning

Collaborative Filtering

Co-Kriging

To Abstract, Understand & Organize

Can we design a unifying (convex) framework for learning Multiple Tasks and their structure?

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Yes!

Can we provide a general meta-strategy for optimization…

…with convergence guarantees?

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Yes!

Can we derive new models of tasks structures from such a framework?

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Yes!

*Can we design a **unifying** (convex) framework for learning multiple-tasks and their structure?*

*Can we provide a general **meta-strategy** for optimization, with convergence guarantees?*

[Ciliberto et al. - ICML 2015]

*Can we derive **new models** of tasks structures from such a framework?*

[Ciliberto et al. - CVPR 2015]

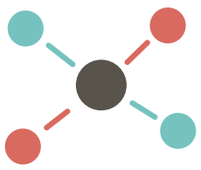
RKHS

for Vector-Valued functions

Examples

A ~ Graph Laplacian

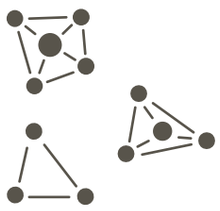
[Evgeniou et al. 2005, Argyriou et al. 2013]



Low dimensional subspace sharing

[Argyriou et al. 2008, Zhang et al. 2010]

$$F(A) = tr(A)$$



Cluster Multi-task learning

[Jacob et al. 2009, kwok et al. 2012]

$$F(A) = \|A\|_c$$

Sparse Kernel Multi-task Learning

[Ciliberto et al. 2015]

$$F(A) = \|A\|_{\ell_1}$$

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[Ciliberto et al. - ICML 2015]

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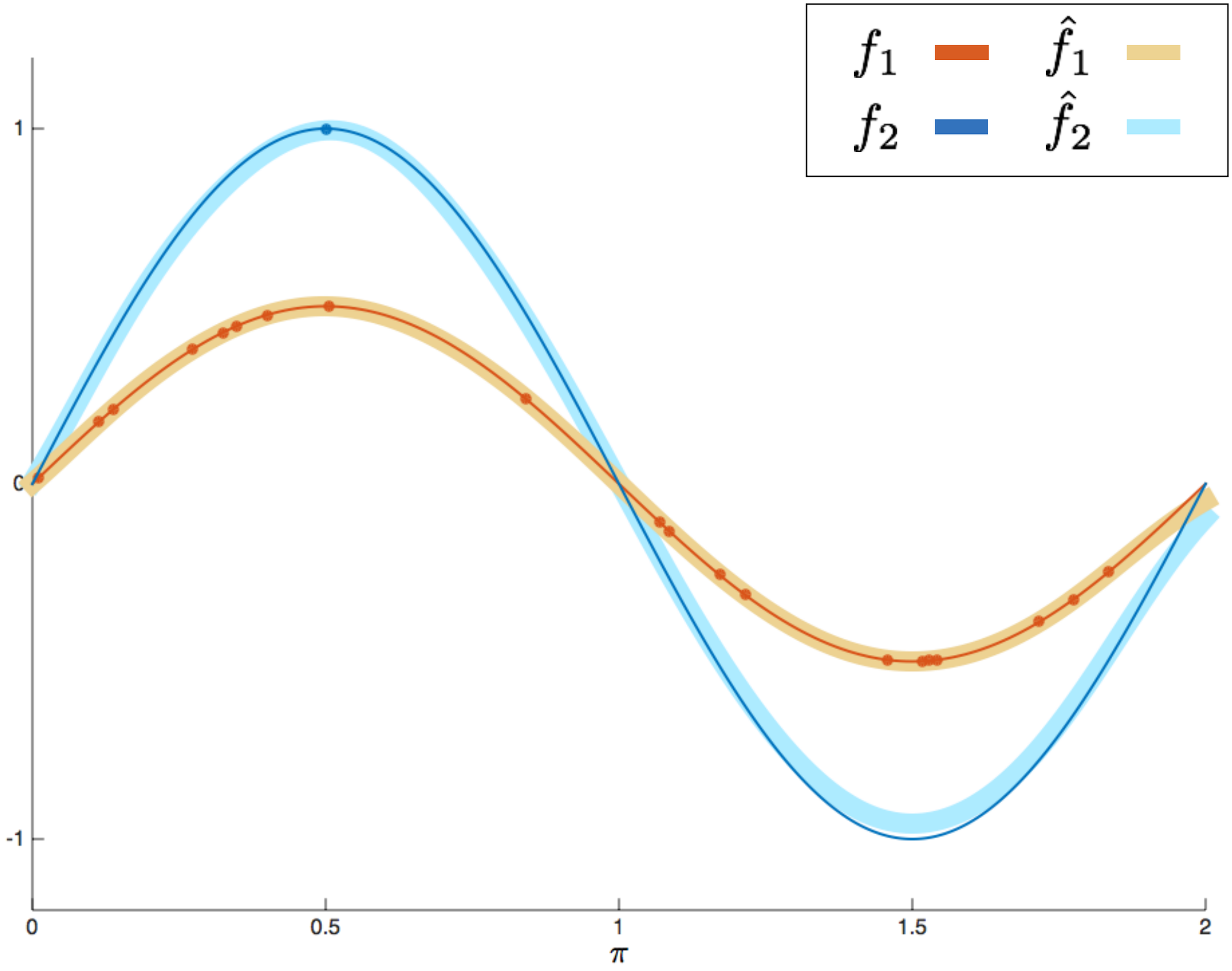
Are we done?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$$k(x, z) A_{ts}$$

$$\Gamma(x, z)_{ts}$$

Can we find a parametrization for all Operator-valued Kernels?

Can we still learn them?

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Can we still learn them?

Spoiler alert: Yes!

[Ciliberto et al. - In Preparation]

Take home messages

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MTL

Multi Task Learning

If tasks are related, solving them jointly can be much more favorable!

Take home messages

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Multi Task Learning

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$\mathbf{k}(\mathbf{x}, \mathbf{z})\mathbf{A}$

RKHS for vector-valued functions

Are the way to go! you can:

Take home messages

MTL

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RKHS for vector-valued functions

Are the way to go! you can:

Impose prior knowledge on the structure

By designing a suitable structure matrix A

Learn the relations!

Imposing a structure penalty F(A) on the problem

Take home messages

MTL

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RKHS for vector-valued functions
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Future Work

More complex intra-task relations
Impose or learn more complex input-output relations