



Build Your Own Tensor Decomposition Model in a Breeze

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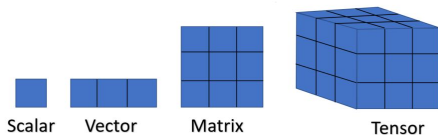
Camera space

2022 CS Postdoc Symposium
Presentation

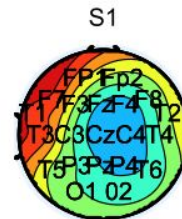
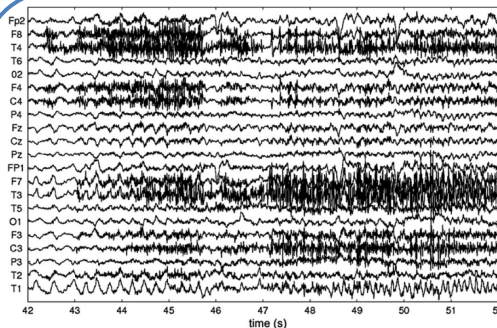


Tensors decompositions have many applications

Camera space



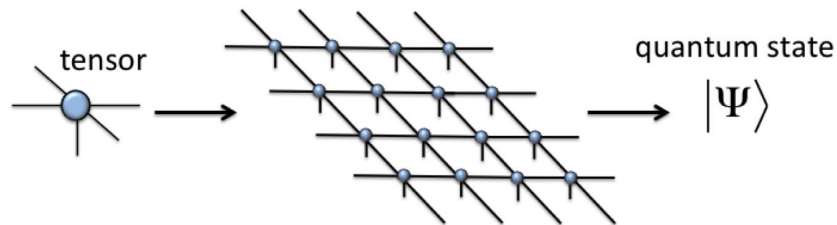
Multiway data



Unsupervised learning: Blind source separation



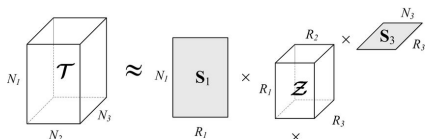
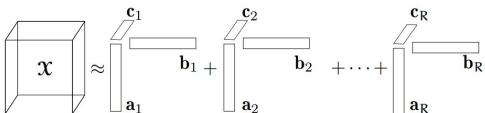
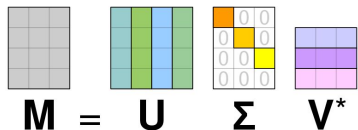
Image and video compression



Quantum physics

A zoo of decompositions and algorithms

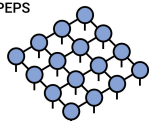
Decompositions



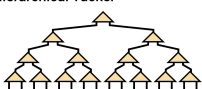
Matrix Product State / Tensor Train



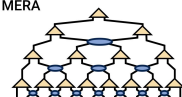
PEPS



Tree Tensor Network / Hierarchical Tucker



MERA



Algorithms

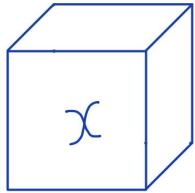
- Bidiagonalization
- Alternating Least-Squares
- CG
- ADMM
- DMRG
- Gradient based
- ...

Every decomposition requires specialized algorithms

All impose linear contractions between factor tensors

Linear

Universe of all possible decompositions



Traditional workflow:



- Analyze model
- Formulate and implement algorithm
- Validate results

Process of days/weeks/months/years

Expert knowledge required

FunFact workflow:



- Write model as (nonlinear) tensor expression
- Factorize data and validate results

Process of minutes/hours

Accessible for non-experts

Behind the scenes of FunFact

Camera space

Frontend: a tensor algebra language through an **embedded domain specific language (eDSL)** that combines NumPy API and generalized **Einstein notations**

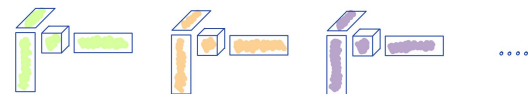
$$c_i = a_{ij} b_j$$

$$c_i = \sum_j a_{ij} b_j$$

Backend: modern NLA libraries that support **autograd**



Algorithm: stochastic gradient descent with multi-replica learning



```
!pip install funfact
import funfact as ff
```

install from PyPI and load

```
a = ff.tensor('a', 50, 3)
b = ff.tensor('b', 3, 20)
i, j, k = ff.indices('i, j, k')
```

declare tensors and indices

```
tsrex = a[i, k] * b[k, j]
```

write tensor expression

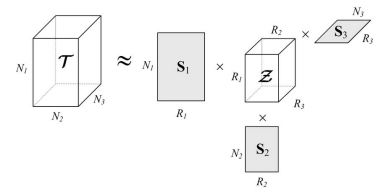
Lazy evaluation: writing down a tensor expression does not trigger immediate evaluation. Rather, the AST of the calculation is saved for future use.

```
target = load_data(...)
ff.factorize(target, tsrex)
```

factorize target tensor

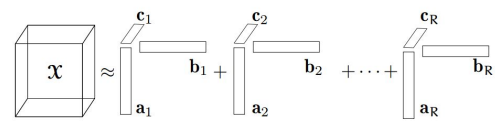
Tucker decomposition

$$\text{tucker} = Z[r1, r2, r3] * S1[r1, n1] * S2[r2, n2] * S3[r3, n3]$$



Tensor-rank decomposition

$$\text{tensor_rank} = (a[i, \sim r] * b[j, r]) * c[k, r]$$



Tensor train decomposition

$$\text{tensor_train} = G1[i1, r1] * G2[i2, r1, r2] * G3[i3, r2, r3] * G4[i4, r3, r4] * G5[i5, r4, r5] * G6[i6, r5]$$

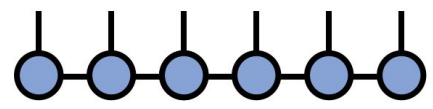


Image compression through nonlinear factorization

Camera space

SVD gives the best rank- r approximation

$$M = U\Sigma V^*$$

$$M \approx U_r \Sigma_r V_r^*$$

`U, S, V = np.linalg.svd(img)`

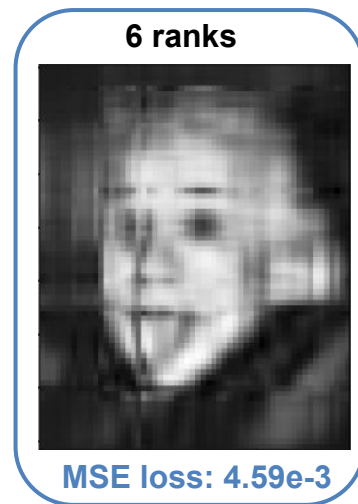
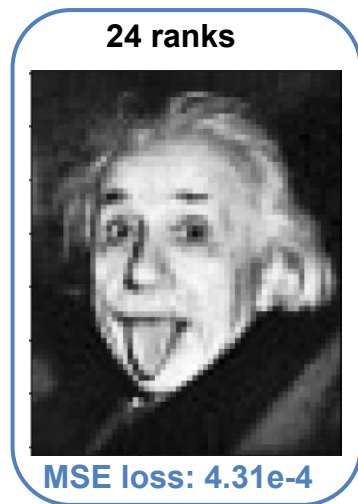
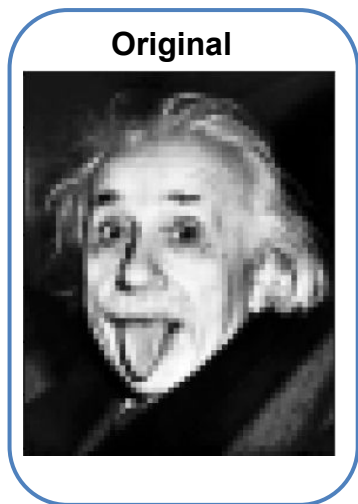


Image compression through nonlinear factorization

Camera space

FunFact finds the same solution

```
low_rank = u[i, r] * v[j, r]
```

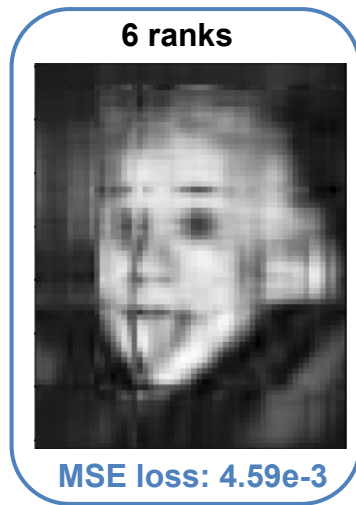
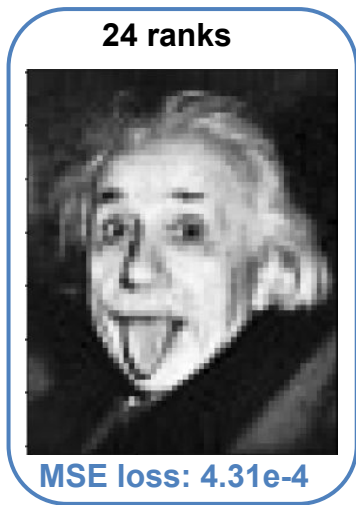
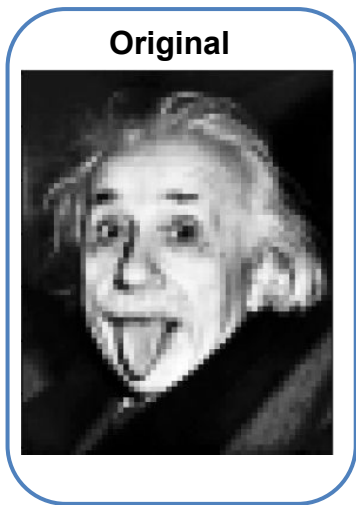


Image compression through nonlinear factorization

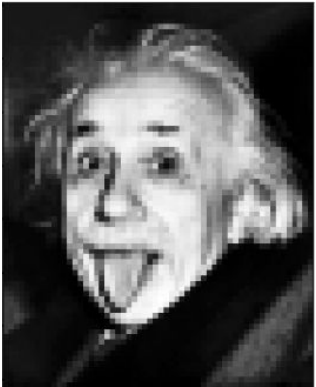
Camera space

```
rbf = ff.exp(-(u[i, ~k] - v[j, ~k])**2) * a[k] + b[[]]
```

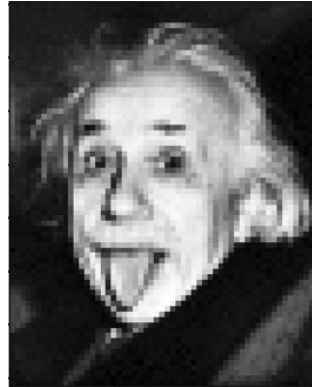
$$A_{ij} \approx \exp \left(- \left(\mathbf{u}_{i\tilde{k}} - \mathbf{v}_{j\tilde{k}} \right)^2 \right) \mathbf{a}_k + \mathbf{b}$$

arXiv:2106.02018

Original



24 ranks



MSE loss: 9.18e-5

12 ranks



MSE loss: 1.54e-3

6 ranks

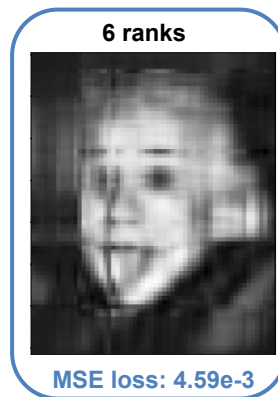
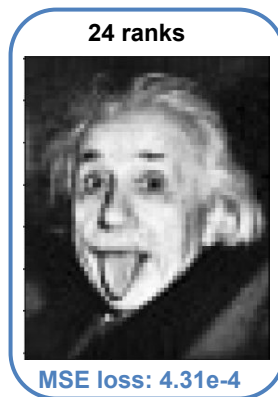


MSE loss: 4.22e-3

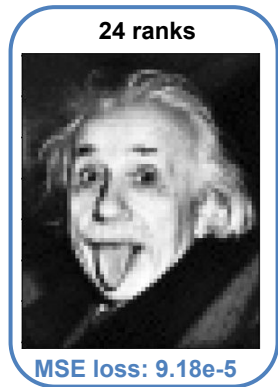
Nonlinear models achieve lower loss for same data complexity

Camera space

SVD



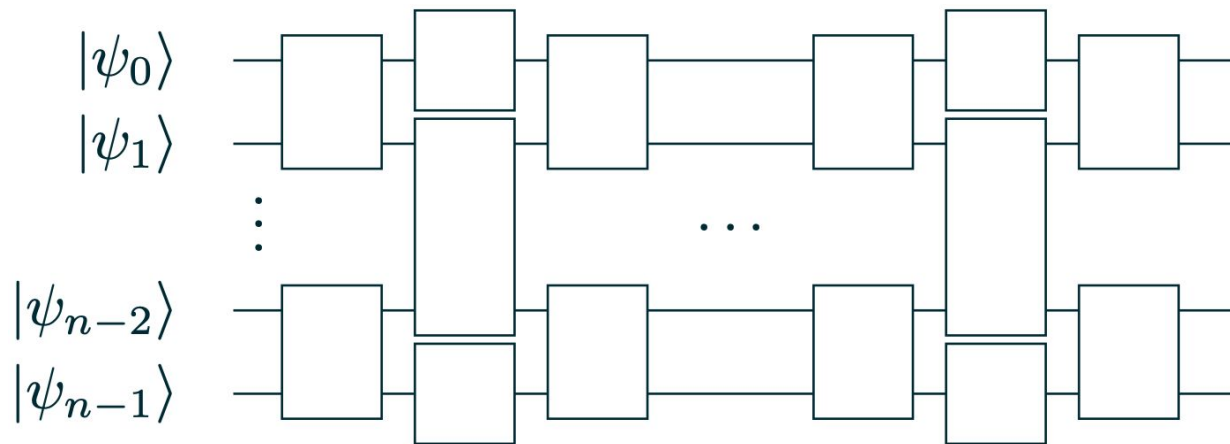
RBF



Quantum circuit compilation as a tensor decomposition

Camera space

- Quantum circuit synthesis or compilation is the task of finding a quantum gate representation for a given unitary operator
- This problem can be formulated as a tensor decomposition problem

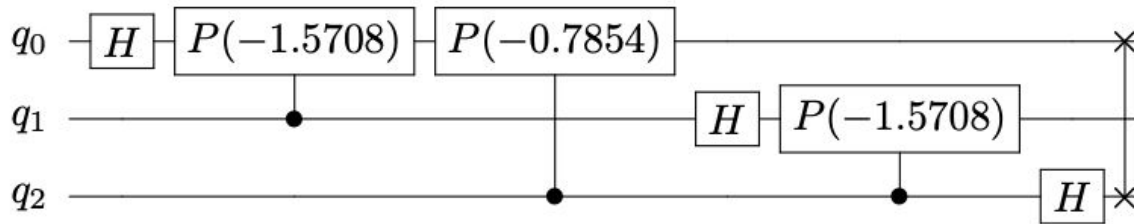


Quantum Circuit Synthesis of Fourier Transform

Camera space

Quantum Fourier Transform DOI:10.1002/nla.2331

- $O((\log N)^2)$ circuit is known

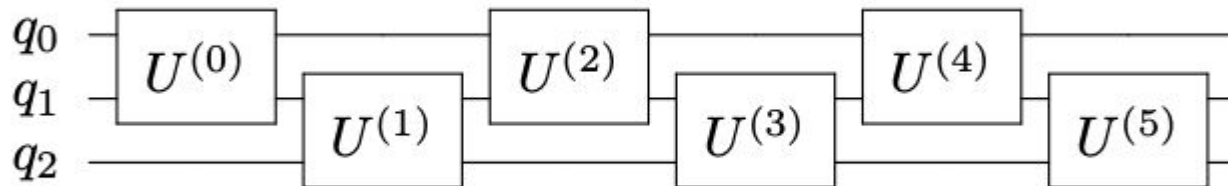


- Might not correspond to hardware qubit topology

Nearest-Neighbor Connectivity

Camera space

- The simplest topology is nearest-neighbor connectivity



```
def two_qubit_gate(i: int, n: int):  
    G = ff.tensor(4, 4, prefer=cond.Unitary)  
    return ff.eye(2**i) & G & ff.eye(2**(n-i-2))
```

```
circuit3 = two_qubit_gate(1, 3) @ \  
two_qubit_gate(0, 3) @ \  
two_qubit_gate(1, 3) @ \  
two_qubit_gate(0, 3) @ \  
two_qubit_gate(1, 3) @ \  
two_qubit_gate(0, 3)
```

Optimizing the circuit as a tensor expression

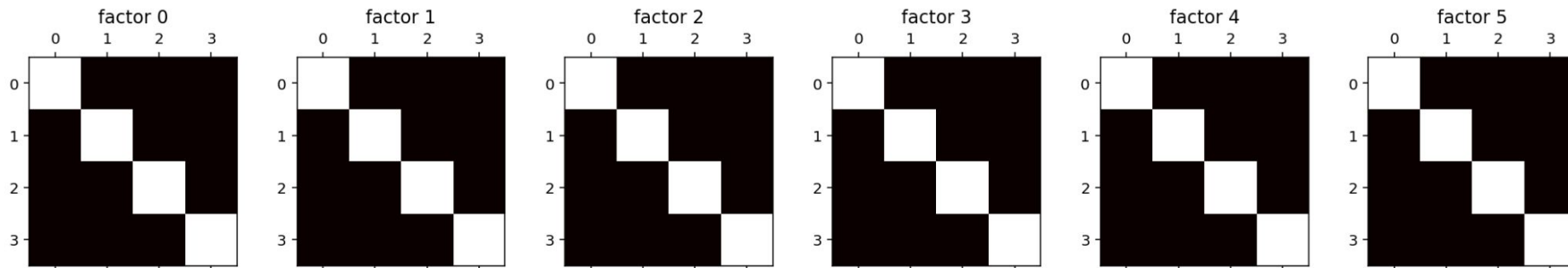
Camera space

```
circuit3_fac = ff.factorize(QFT3, circuit3, ...)
```

loss: 0.009713371542746886

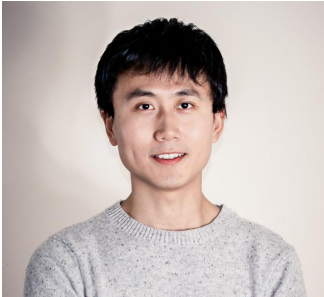
penalty: 8.032669575186446e-05

Unitariness of factor matrices: $|U^\dagger U|$

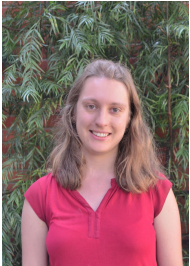


FunFact is developed in collaboration with:

- Yu-Hang Tang (SSG)



- Liza Rebrova (previous contributor)



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LDRD No. DE-AC02-05CH11231**



- FunFact is a **rich and flexible** language for (non-)linear **tensor algebra** expressions
- FunFact can solve the **inverse problem** thanks to modern NLA backends such as JAX and PyTorch
- Dramatically **reduced time-to-algorithm** for new tensor factorization models

Released V1.0RC under BSD license

Find out more at:

- funfact.readthedocs.io
- github.com/yhtang/FunFact/
- pypi.org/project/funfact/

We're looking for users and applications!

Don't hesitate to reach out at dcamps@lbl.gov