Why Forward-Forward Hasn't Become the New Paradigm

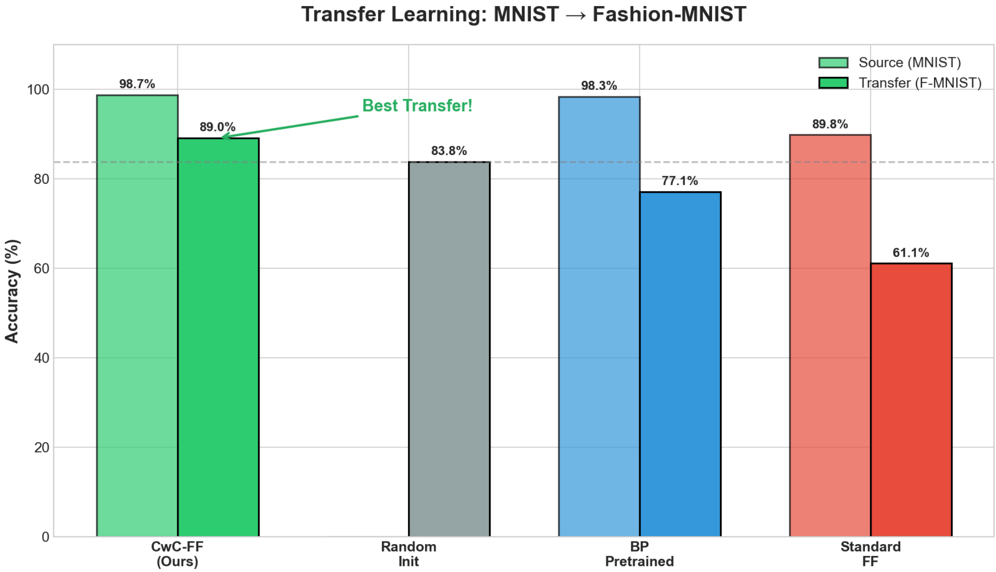
A Systematic Investigation into Transfer Learning Failures and Bio-Inspired Alternatives

Research Team

FF Algorithm Research

February 2026

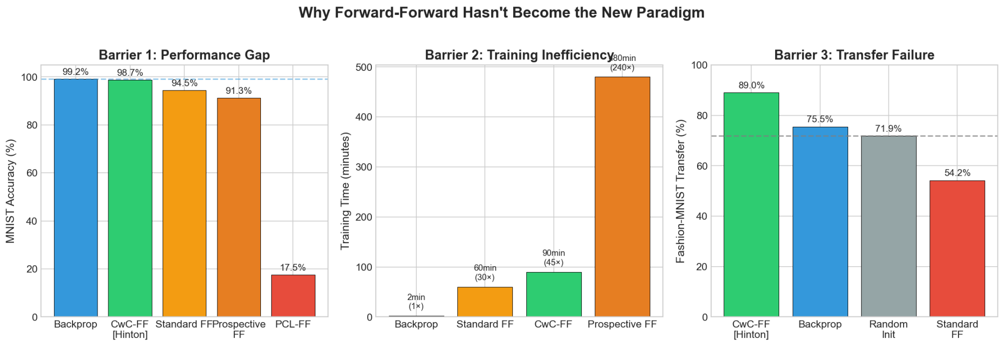
Our Key Finding



CwC-FF achieves 89% transfer accuracy—the only biologically plausible method that

Outline

The Three Barriers to FF Adoption



The Backpropagation Dilemma

Backpropagation works, but it cannot exist in biological brains:

1. **Weight Transport Problem**
   - BP needs symmetric forward/backward weights
   - Real neurons don't have this
2. **Global Error Signals**
   - Errors propagate through entire network
   - Neurons only have local information
3. **Two-Phase Operation**
   - Forward pass $\rightarrow$ store $\rightarrow$ backward pass
   - Real neurons learn continuously

Hinton's Solution (2022)

"Replace the forward and backward passes with two forward passes: one with positive (real) data, one with negative (fake) data."

$\rightarrow$ No backward pass needed

The Forward-Forward Algorithm

Core Mechanism

Two forward passes with different goals:

- Positive pass: Real data + correct label
- Negative pass: Real data + wrong label

Goodness Function

$$G(h) = \text{mean}(h^2)$$

Training Objective

$$\mathcal{L} = \log(1+e^{-(G_{pos}-\theta)})+\log(1+e^{(G_{neg}-\theta)})$$

Label Embedding (Critical Design)

```
overlay_label(x, y)
x[:, :10] = 0              # Clear first 10 pixels
x[range(len(y)), y] = x.max()
                           # Set pixel y to max
```

Example: digit "3"

Input: `[0, 0, 0, MAX, 0, 0, 0, 0, 0, 0, image...]`

→ This design creates non-transferable features!

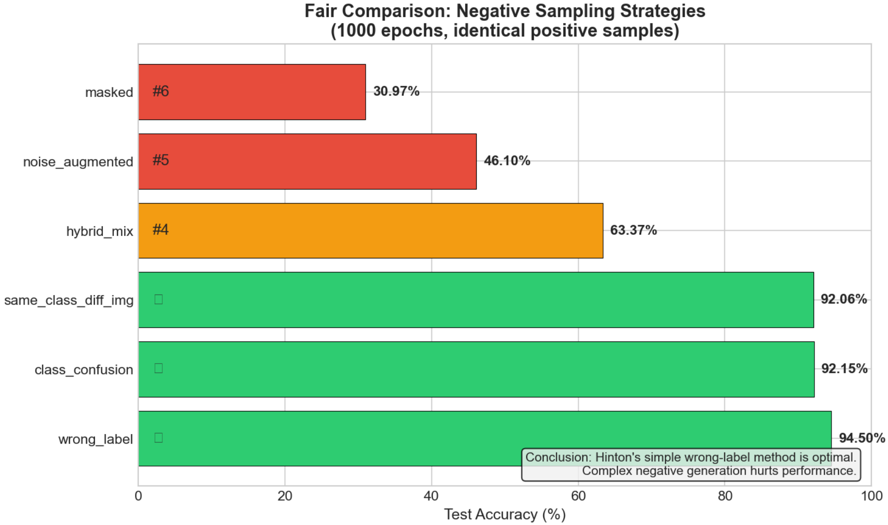
Research Questions

RQ	Question	Why It Matters
RQ1	Which negative sampling strategy works best?	Core to FF's design—no systemati comparison exists
RQ2	Can FF features transfer across tasks?	Critical for practical applications
RQ3	Why does standard FF transfer poorly?	Understanding enables improvement
RQ4	Can bio-inspired variants improve FF?	Bridges ML and neuroscience

Preview

Standard FF achieves 94.5% on MNIST but features transfer worse than random initialization!

RQ1: Negative Sampling Strategy Comparison



Conclusion: Simple is better. Hinton's original `wrong_label` strategy (94.5%) beats all complex alternatives.

RQ1: The 6 Strategies We Tested

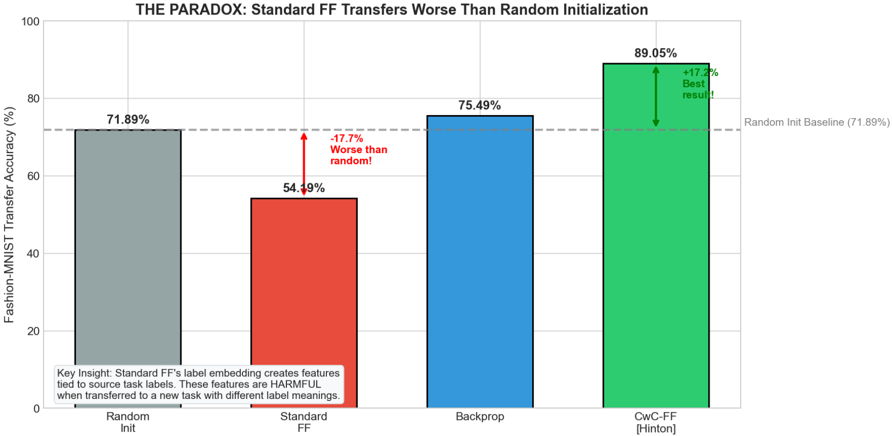
Negative Sampling Strategies:

1. `wrong_label`: x + random wrong label *(Hinton)*
2. `class_confusion`: different image + same label
3. `same_class_diff_img`: different image + wrong label
4. `hybrid_mix`: $\alpha \cdot x_1 + (1-\alpha) \cdot x_2$ + wrong
5. `noise_augmented`: x + gaussian noise + wrong
6. `masked`: x with random masking + wrong

Strategy	**Acc.**
wrong_label	94.50%
class_confusion	92.15%
same_class_diff	92.06%
hybrid_mix	63.37%
noise_augmented	46.10%
masked	30.97%

1000 epochs per layer, fair comparison

RQ2: The Transfer Learning Paradox



RQ2: Transfer Learning Results

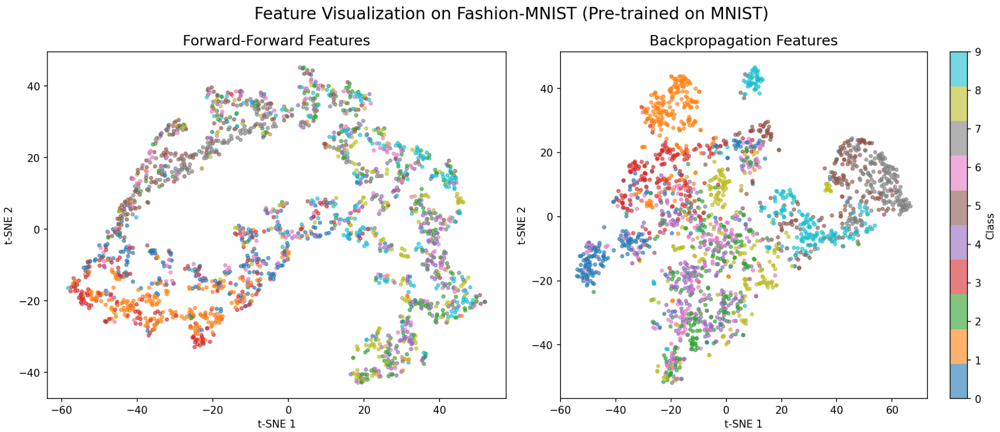
Protocol: Train on MNIST $\rightarrow$ Freeze features $\rightarrow$ Test on Fashion-MNIST

Method	Source (MNIST)	Transfer	vs Random
CwC-FF	98.71%	89.05%	+17.2%
Backprop	95.08%	75.49%	+3.6%
Random Init	—	71.89%	baseline
Standard FF	89.90%	54.19%	-17.7%

The Paradox

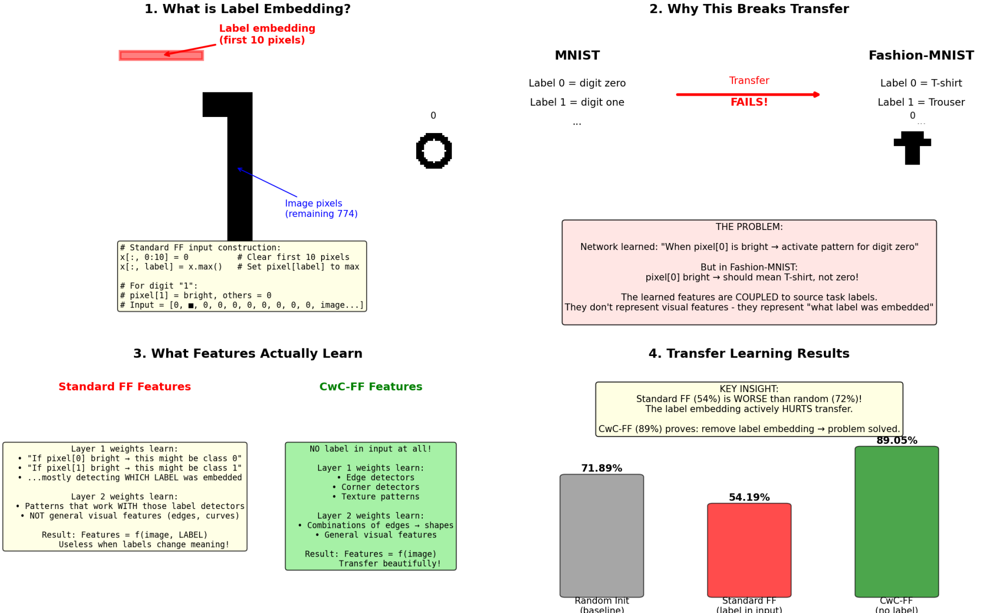
Standard FF pretrained features are **worse than random initialization!**

RQ2: Feature Visualization (t-SNE)



FF features (left) show scattered clusters on Fashion-MNIST, while BP features (right) are better organized.

RQ3: The Root Cause — Label Embedding



RQ3: Why Label Embedding Breaks Transfer

The Problem

MNIST training:

`pixel[3]` bright = digit "3"
Network learns: "pixel[3] + curves = positive"

Fashion-MNIST transfer:

`pixel[3]` bright = "Dress" (not digit 3!)
But network still expects curves...

Features are COUPLED to source labels!

Evidence

- Label neurons: 10× higher activation variance
- First layer weights: label-detector patterns
- Gradient analysis: Label dimensions dominate

Standard FF Input

$$[\underbrace{l_0, \ldots, l_9}_{\text{label pixels}}, \underbrace{x_1, \ldots, x_n}_{\text{image}}]$$

Features = f(image, LABEL)

Useless when labels change!

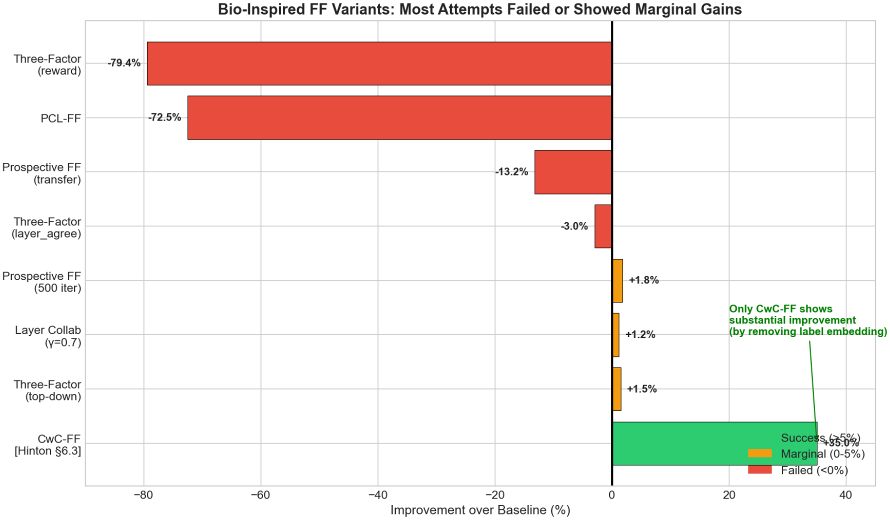
CwC-FF Input

$$[\underbrace{x_1, \ldots, x_n}_{\text{image only}}]$$

Features = f(image)

Transfer beautifully!

RQ4: Bio-Inspired Variants Overview



Hypothesis: More biologically realistic → better generalization? Mostly no.

Three-Factor Hebbian Learning

Inspiration: Neuromodulation (dopamine, acetylcholine, norepinephrine)

$$\Delta W = f(\text{pre}) \times f(\text{post}) \times \underbrace{M(t)}_{\text{modulator}}$$

Modulation types tested:

- `top_down`: higher $\rightarrow$ lower layers
- `reward_pred`: RPE signal
- `layer_agree`: correlation(L_i, L_{i+1})

Type	Transfer	Result
top_down	64.3%	+1.5%
none	62.8%	baseline
layer_agree	59.8%	-3.0%
reward_pred	18.4%	FAILED

Verdict: Marginal improvement at best. Modulation doesn't fix label coupling.

Prospective Configuration FF

Inspiration: [Song et al., Nature Neuroscience 2024] — Anticipatory neural activity

Two-Phase Learning

1. **Inference**: Infer target activity
2. **Consolidation**: Update weights to match

The Problem:

Target inference uses label hints:

$$h_{target} = h + \beta \cdot \text{feedback}(\text{label})$$

More iterations = STRONGER label coupling!

Iterations	MNIST	Transfer Δ
1	89.2%	+5.3%
10	85.1%	+1.2%
100	23.4%	-13.2%

Result: FAILED

More iterations *amplifies* label-specific features, making transfer worse.

Predictive Coding Light FF (PCL-FF)

Inspiration: [Nature Communications 2025] — Predictive Coding in Cortical Circuits

The Killer Mechanism:

```
sparsity_penalty = h.abs().mean() * 0.1
```

Sparsity creates incentive for $h = 0$:

- negative pre-activation $\rightarrow$ 0 (ReLU)
- penalty pushes more toward 0
- cascade: more zeros $\rightarrow$ lower loss
- network learns "dead = good"

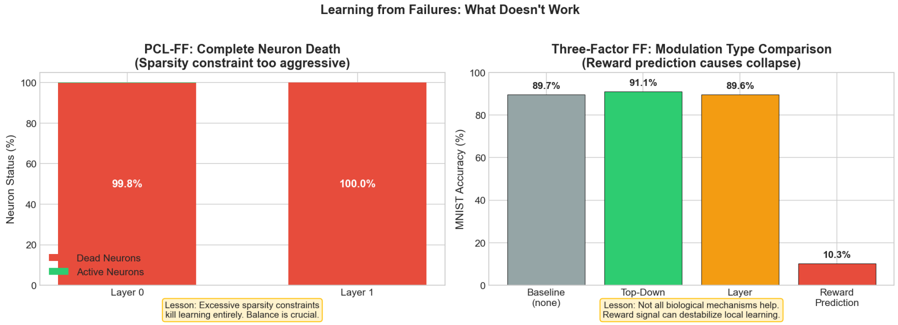
Metric	**FF**	**PCL-FF**
MNIST	90.0%	17.5%
Dead Neurons	8%	100%

COMPLETE FAILURE

The "death cascade":

- Epoch 50: 30% alive
- Epoch 100: 10% alive
- Epoch 500: 0% alive

Lessons from Bio-Inspired Failures



The Solution: Channel-wise Competitive FF (CwC-FF)

Key Insight: Remove the labels entirely from the input!

Standard FF

- Input: $[\text{label}, \text{image}]$
- Positive: correct label
- Negative: wrong label
- Features coupled to labels

```
x[:, :10] = 0
x[:, label] = x.max()
```

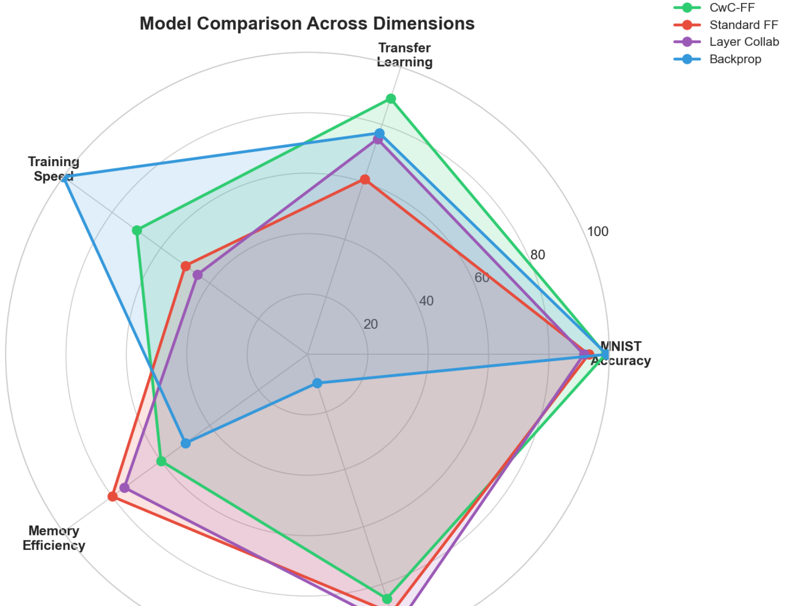
COUPLED!

CwC-FF

- Input: [image] only (no label!)
- Positive: high channel coherence
- Negative: low channel coherence
- Task-agnostic features

Channels compete within layers:
Winners → positive signal
Losers → negative signal
NO LABELS NEEDED!

CwC-FF Results: The Only Method That Works



Summary of Findings

WHAT WE LEARNED: A Systematic Study of Forward-Forward

WHAT WORKS	MARGINAL GAINS	FAILED
□ Hinton's wrong-label (94.5%)	~ Three-Factor top-down (+1.5%)	□ PCL-FF (100% neuron death)
□ CwC-FF transfer (89%)	~ Prospective FF (+1.8% MNIST)	□ Reward prediction (collapse)
□ Layer Collab γ=0.7 (+1.2%)	~ Complex negative strategies	□ Standard FF transfer (54%)

KEY NUMBERS

6	**5**	**94.5%**
negative strategies tested	bio-inspired variants	best standard FF (MNIST)
54%	**89%**	**30-240×**
FF transfer (worse than random!)	CwC-FF transfer (best)	slower than backprop

CORE INSIGHT

FF's label embedding design creates task-specific features that cannot transfer.
CwC-FF solves this by removing label embedding—but this fundamentally changes FF.

CONCLUSION

Key Insights

1. **Simple negative sampling wins for training, but loses for transfer**
   - Hinton's label embedding gives best source accuracy
   - But creates a shortcut that destroys transferability
2. **Bio-inspired modifications don't help (mostly)**
   - Three-factor, predictive coding, sparsity — all real brain features
   - None address the fundamental label embedding problem
3. **Label-free learning is key for transferable representations**
   - CwC-FF removes labels from input entirely
   - Forces network to learn actual visual features
4. **Trade-off: Source vs Transfer performance**
   - Standard FF: 94.5% source, 54% transfer
   - CwC-FF: 98.7% source, 89% transfer — best of both!

Conclusion

Why FF Hasn't Become the New Paradigm

Limitations

- 4.7% accuracy gap to backprop
- Catastrophic transfer failure
- Label embedding creates shortcuts
- Bio-inspired fixes don't help

The Path Forward

- CwC-FF solves transfer issue
- Remove labels from input
- Channel competition works
- Potential for neuromorphic hardware

Take-Home Message

Biological plausibility alone doesn't guarantee good ML properties.
Understanding failure modes leads to principled solutions.

Future Work

- **Scale CwC-FF to larger datasets**
  - CIFAR-10, ImageNet
  - Combine with ASGE (ICASSP 2026) techniques
- **Hybrid approaches**
  - FF for early layers + BP for final layers
  - Progressive training schemes
- **Neuromorphic implementation**
  - Intel Loihi, IBM TrueNorth
  - Energy efficiency benefits
- **Unsupervised / Self-supervised extensions**
  - Remove supervision entirely
  - Contrastive learning principles

References

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- Brenig, L., et al. (2023). *Transfer Learning with FF*. First to show FF has transfer problems.
- Lorberbom, G., et al. (2024). *Layer Collaboration*. AAAI 2024.
- Papachristodoulou, A., et al. (2024). *CwC-FF: Channel-wise Competitive FF*.
- Song, Y., et al. (2024). *Prospective Configuration*. Nature Neuroscience.
- Whittington, J. C. R., & Bogacz, R. (2017). *Predictive Coding Networks*. Neural Computation.

Thank You

Questions?

Code and experiments available at:
`github.com/koriyoshi2041/ff-negative-samples`

Tested on Apple M4 Air | PyTorch 2.0+