

# ML-Guided IBP Reduction

Neural Network Guided Integration-by-Parts Reduction of  
Feynman Integrals

Two-Loop Triangle-Box Topology

## The Problem

- ▶ **IBP reduction:** Express complex Feynman integrals as linear combinations of simpler “master” integrals
- ▶ **Challenge:** Exponential search space of IBP identities
- ▶ **Traditional approaches:** Laporta algorithm, Kira, FIRE

# The Memory Wall

Traditional IBP codes hit **memory limits** as integrals grow more complex:

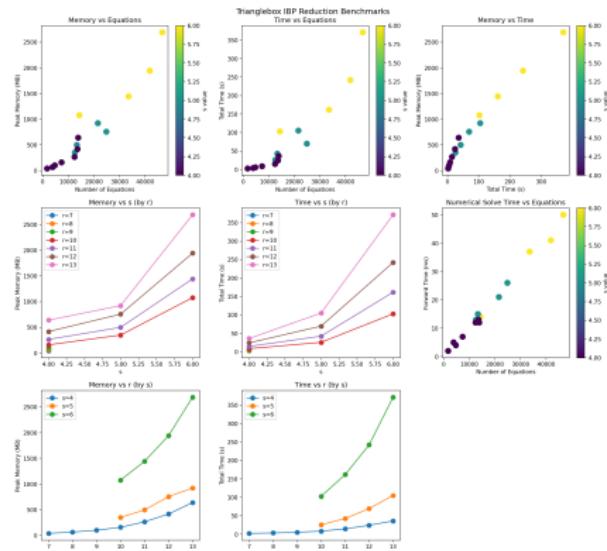


Figure 1: Kira Memory Scaling

*Kira benchmarks: Memory grows exponentially with integral weight ( $r$ ), reaching 2.5+ GB for  $r=13$ .*

## Our Solution

- ▶ **ML-guided beam search:** Train a neural network to score IBP actions
- ▶ **Hierarchical reduction:** Process sectors from highest to lowest
- ▶ **Parallel execution:** Distribute across Condor cluster for ~10x speedup
- ▶ **Constant memory:** Each one-step reduction is independent - no system accumulation

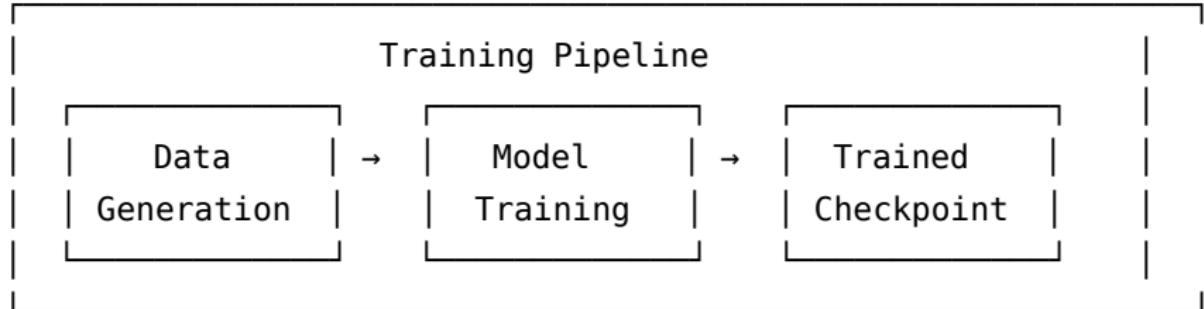
## Key Results

### Triangle-Box Topology (arXiv:2502.05121)

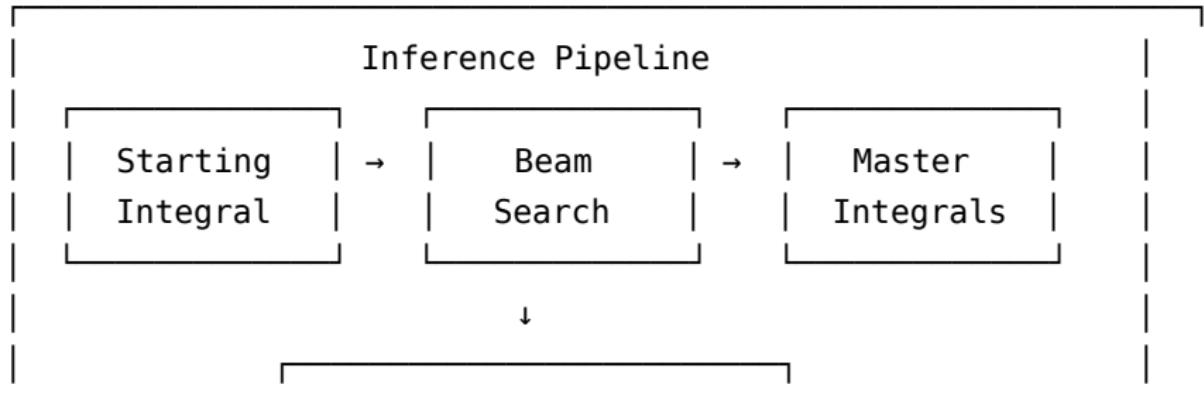
Integral	Weight	Sequential	Parallel	Speedup	Masters
$I[2,0,2,0,1,1,0]$	(6,0)	5 min	-	-	4
$I[1,1,1,1,1,1,-3]$	(6,3)	73 min	12 min	6x	16
$I[3,2,1,3,2,2,-6]$	(13,6)	<b>~20 hr</b>	<b>115 min</b>	<b>~10x</b>	16

- ▶ Results match Kira exactly
- ▶ Reduces to exact 16 paper masters from arXiv:2502.05121

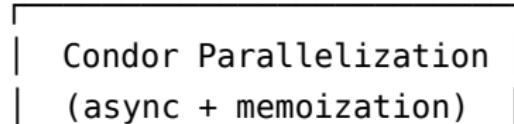
# System Architecture



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## Part 1: Data Generation

# Data Generation: Scrambling Approach

## Key Insight

Instead of collecting reduction trajectories (expensive), **reverse the process**: 1. Start from master integrals 2. Apply random IBP identities to increase complexity 3. Record each step - becomes training data when reversed

## Constraints During Scrambling

- ▶ Only apply IBPs that don't introduce higher-sector integrals
- ▶ Stay within target sector and subsectors
- ▶ Ensures training data reflects valid reduction paths

# Data Generation: Coverage

## Sector Coverage

- ▶ All 63 non-trivial sectors covered
- ▶ Uses 16 paper masters for their respective sectors
- ▶ Uses corner integrals for remaining sectors

## Dataset Statistics

Split	Samples	Size
Train	946,168	3.8 GB
Validation	118,271	480 MB
Test	~118,000	480 MB

# Data Format

Each training sample contains:

```
{  
    'sector_mask': [1,0,1,0,1,1],  # 6-bit sector encoding  
    'expr': [                      # Current expression  
        ([1,0,2,0,1,1,0], 107),     # (integral, coefficient)  
        ([1,0,1,0,1,1,0], 303),  
        ...  
    ],  
    'subs': [                      # Substitution history  
        (key_integral, [(repl_int1, coeff1), ...]),  
        ...  
    ],  
    'target_integral': [1,0,2,0,1,1,0], # Integral to eliminate  
    'valid_actions': [(ibp_op, delta), ...],  
    'label': 3  # Index of correct action  
}
```

## Part 2: Model Architecture

# Model: IBPActionClassifierV5

## Overview

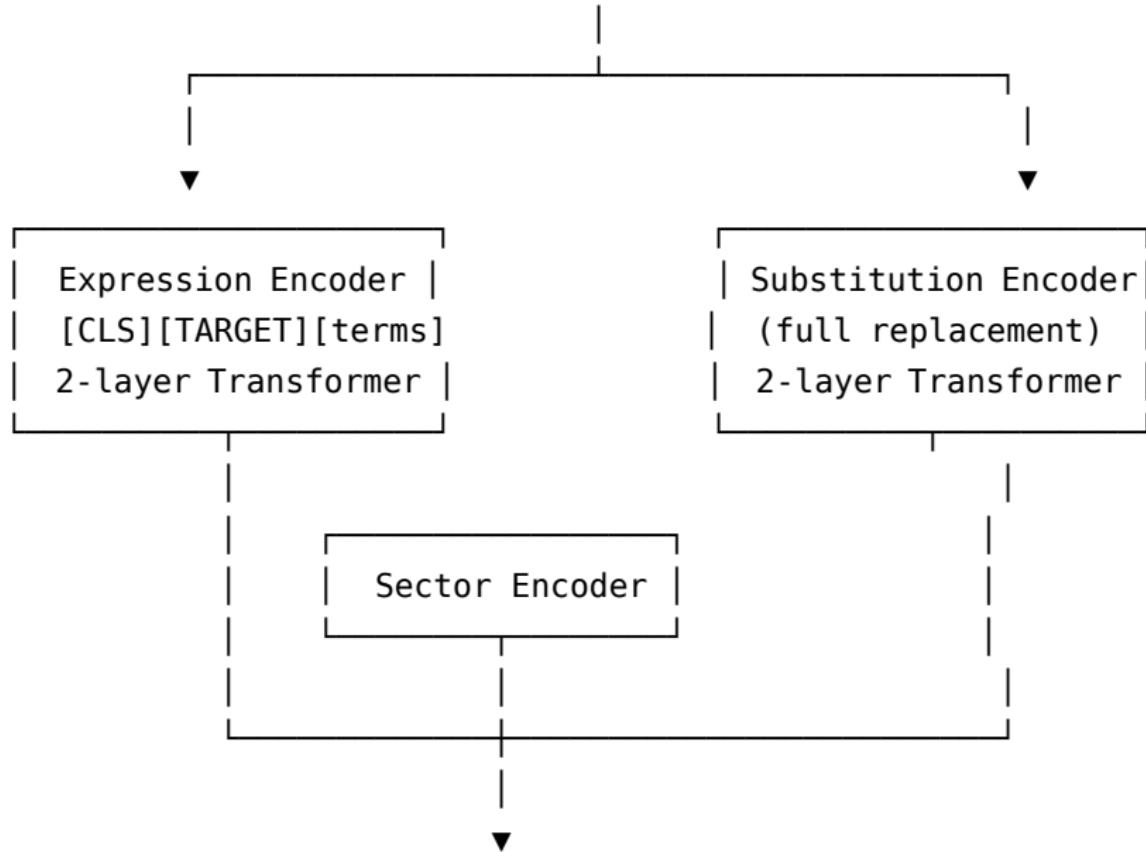
- ▶ **Task:** Score candidate IBP actions given current reduction state
- ▶ **Architecture:** Transformer-based with specialized encoders
- ▶ **Parameters:** 7.7M
- ▶ **Best validation accuracy:** 90.77%

## Key Innovation (V5)

Full substitution encoding - encode not just the key integral but the complete replacement expression

# Model Architecture Diagram

Inputs: Expression, Target, Substitutions, Sector, Actions



## Component Details

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Component	Purpose	Architecture
<b>Expression Encoder</b>	Encode current expression + target	2-layer Transformer
<b>Substitution Encoder</b>	Encode reduction history	2-layer Transformer + attention pooling
<b>Sector Encoder</b>	Condition on target sector	Embedding + projection
<b>Cross-Attention Scorer</b>	Score actions by attending to expression	2-layer cross-attention

---

## Model Hyperparameters

- ▶ Embedding dimension: 256
- ▶ Attention heads: 4
- ▶ Total parameters: 7,696,709

## Part 3: Training

# Training Configuration

```
epochs = 30
batch_size = 256
learning_rate = 0.0004
weight_decay = 1e-5
optimizer = AdamW
```

## Training Results

- ▶ **Best checkpoint:** Epoch 22
- ▶ **Validation accuracy:** 90.77% (top-1)
- ▶ **Top-5 accuracy:** ~98%
- ▶ **Training time:** ~800s per epoch on GPU

# Training Curves

## Key Observations

- ▶ Model converges by epoch 20-25
- ▶ Validation accuracy plateaus at ~91%
- ▶ No significant overfitting observed
- ▶ Top-5 accuracy very high (~98%) - beam search can recover from top-1 mistakes

## Part 4: Beam Search Inference

# Beam Search Algorithm

```
def beam_search(start_integral, beam_width=20):
    beam = [start_state]

    while not all_masters(beam[0]):
        candidates = []
        for state in beam:
            for action in get_valid_actions(state):
                score = model.score(state, action)
                new_state = apply_action(state, action)
                candidates.append((new_state, score))

        # Keep top-k by score
        beam = sorted(candidates, key(score))[:beam_width]

    return beam[0]
```

# Beam Search Optimizations

## P1: Equation Caching ( $\sim 3\text{-}10x$ speedup)

- ▶ IBP equation generation is expensive (sympy operations)
- ▶ Cache `get_raw_equation` results
- ▶ Reuse across beam states with shared history

## P2: Batched Inference ( $\sim 50x$ speedup)

- ▶ Prepare all action candidates as numpy arrays
- ▶ Single batched forward pass through model
- ▶ Eliminates per-action inference overhead

## Combined Effect

- ▶ Per-step time: 10-90s  $\rightarrow$  0.1-5s
- ▶ Makes deep reductions feasible

# Hierarchical Reduction Strategy

## Algorithm

1. Find highest-level sector with non-master integrals
2. Run beam search to eliminate all non-masters in that sector
3. Move to next highest sector
4. Repeat until only masters remain

Example: I[2,0,2,0,1,1,0]

Sector	Level	Steps
53	4	53
52	3	17
49	3	4
37	3	42
21	3	46
...	...	...
<b>Total</b>	-	<b>176</b>

# Beam Restart Strategy (V11+)

## Problem

After weight improvement, beam often contains suboptimal states that will never succeed

## Solution: Beam Restart

1. Run beam search until weight improves
2. **Stop and restart** with only the best state
3. Prunes dead ends, enables deeper exploration

## Impact

- ▶ Essential for high-weight integrals
- ▶  $I[1,1,1,1,1,1,-3]$ : 1,416 steps across 45 sectors
- ▶  $I[3,2,1,3,2,2,-6]$ : 46,345 steps across 62 sectors

## Part 5: Parallelization

# Parallelization Motivation

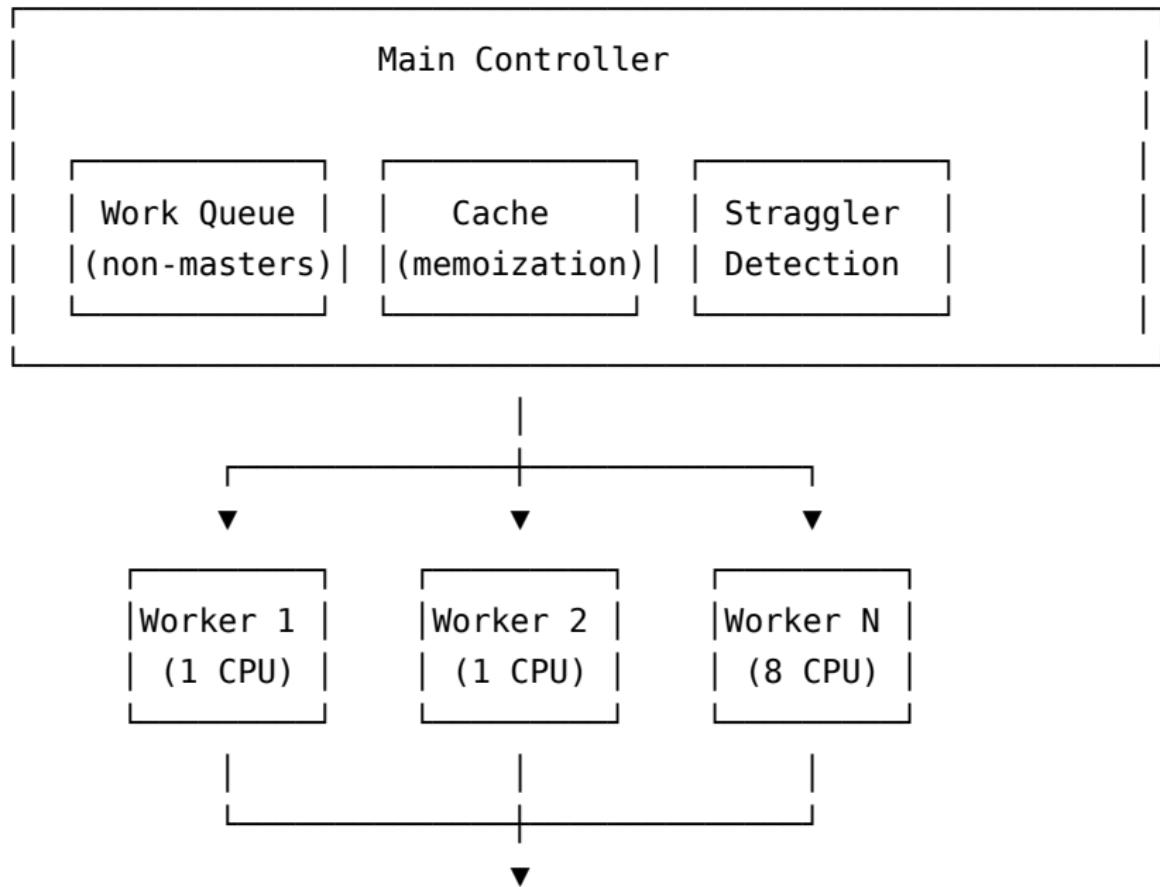
## The Bottleneck

- ▶ Sequential reduction of  $I[3,2,1,3,2,2, -6]$  takes ~20 hours
- ▶ Single-threaded beam search on CPU
- ▶ Many independent integrals could be processed in parallel

## Key Insight

Each one-step reduction is independent - distribute across workers!

# Async Parallel Architecture



# Key Parallelization Features

## 1. Async Work Distribution

- ▶ Submit all pending non-masters immediately
- ▶ Don't wait for level synchronization
- ▶ Process results as they arrive

## 2. Memoization Cache

- ▶ Store: integral → reduced expression
- ▶ Avoid redundant work (~55,000 cache hits!)
- ▶ Critical when stragglers produce already-cached results

## 3. Straggler Detection

- ▶ Jobs >30 min are killed and resubmitted
- ▶ Resubmit with 8 CPUs (parallel beam search)
- ▶ Prevents slow integrals from blocking progress

# Parallel Performance

## I[3,2,1,3,2,2,-6] Results

Metric	Value
Time (sequential)	~20 hours
Time (parallel)	<b>115 minutes</b>
<b>Speedup</b>	~10x
Jobs submitted	21,096
Stragglers resubmitted	24
Cache hits	55,075
Final masters	16

## Part 6: Results

## Validation Against Kira

I[2,0,2,0,1,1,0] (Sector 53)

Method	Masters	Result
<b>Kira</b>	4	Reference
<b>Our V5</b>	4	Matches exactly

Our reduction produces the **exact same master basis** as professional IBP software.

## Scaling Results

Integral	Weight	Time	Steps	Masters
I[2,0,2,0,1,1,0]	(6,0)	5 min	176	4
I[1,1,1,1,1,1,-3]	(6,3)	12 min*	1,416	16
I[3,2,1,3,2,2,-6]	(13,6)	<b>115 min*</b>	131,769	16

\*With parallel execution

## Final Reduction Example

$I[3,2,1,3,2,2,-6] \rightarrow 16$  Paper Masters

Final expression (mod 1009):

```
171 * I[1,0,1,1,1,1,0]
854 * I[1,1,0,1,1,1,0]
377 * I[1,1,1,1,1,0,0]
160 * I[-1,1,1,1,1,0,0]
100 * I[0,1,1,1,1,0,0]
647 * I[1,-1,1,0,1,1,0]
9 * I[1,-1,1,1,1,0,0]
... (16 masters total)
```

Matches arXiv:2502.05121 basis exactly!

## Part 7: Conclusions

## Key Contributions

1. **ML-guided IBP reduction** that matches professional software (Kira)
2. **Constant memory usage** - avoids the memory wall of traditional approaches
3. **Hierarchical beam search** with restart strategy for deep reductions
4. **Async parallel execution** with ~10x speedup
5. **Straggler handling** for robust distributed computing
6. **Paper-masters-only mode** for clean minimal basis

# Technical Innovations

## Model

- ▶ Full substitution encoding (V5)
- ▶ Cross-attention action scoring
- ▶ Target-aware expression encoding

## Inference

- ▶ Equation caching (3-10x speedup)
- ▶ Batched model inference (50x speedup)
- ▶ Beam restart strategy

## Parallelization

- ▶ Async one-step distribution
- ▶ Memoization cache ( $\sim 55k$  hits)
- ▶ Automatic straggler resubmission

## Future Work

1. **GPU workers** for faster beam search
2. **Adaptive timeouts** based on sector statistics
3. **More integrals** - test on other two-loop families
4. **Training on successful paths** - use reduction results to improve model
5. **Path optimization** - shorten saved reduction paths

# Code Availability

**Repository:** [github.com/davidshih17/RL\\_IBPrediction\\_claude](https://github.com/davidshih17/RL_IBPrediction_claude)

## Key Files

- ▶ `models/classifier_v5.py` - Model architecture
- ▶ `scripts/eval/hierarchical_reduction_async.py` - Parallel reduction
- ▶ `scripts/eval/reduce_integral_onestep_worker.py` - Condor worker
- ▶ `docs/parallelization.md` - Detailed documentation

# Thank You

Questions?

Contact

- ▶ Repository:  
[github.com/davidshih17/RL\\_IBPrediction\\_claude](https://github.com/davidshih17/RL_IBPrediction_claude)
- ▶ arXiv: 2502.05121 (paper masters reference)