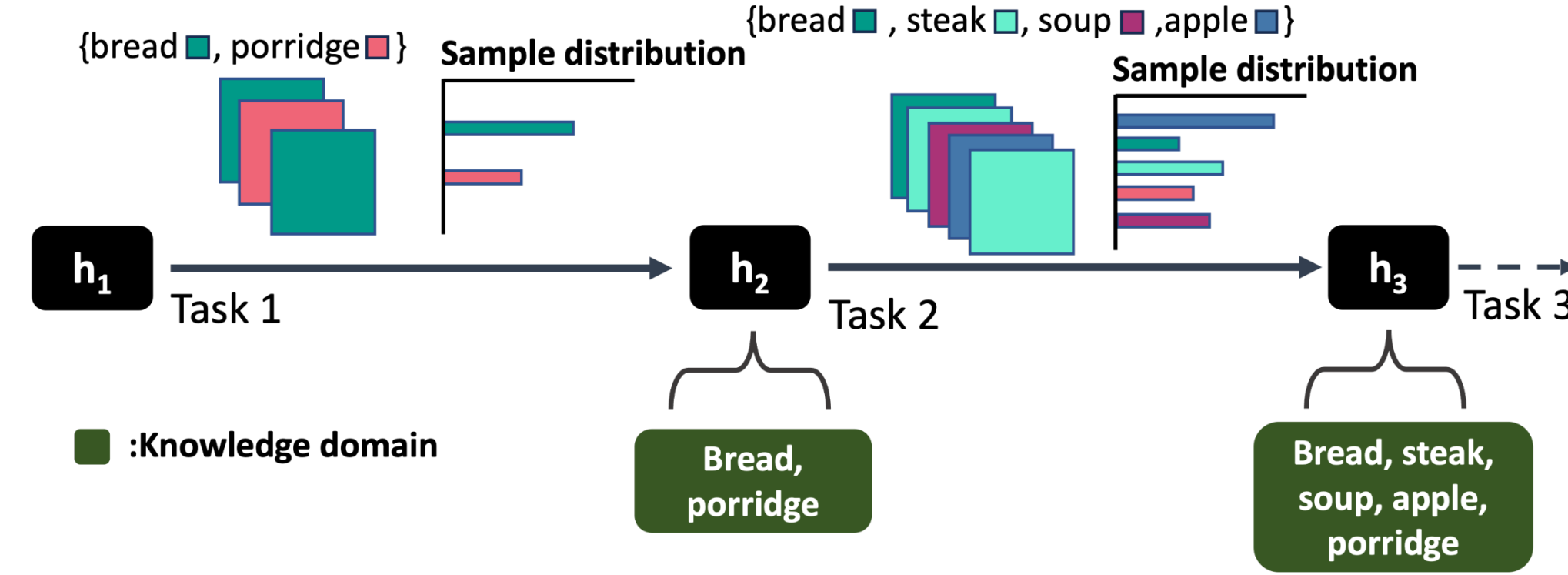


# Online Class-Incremental Learning For Real-World Food Image Classification

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## Online Class Incremental Learning

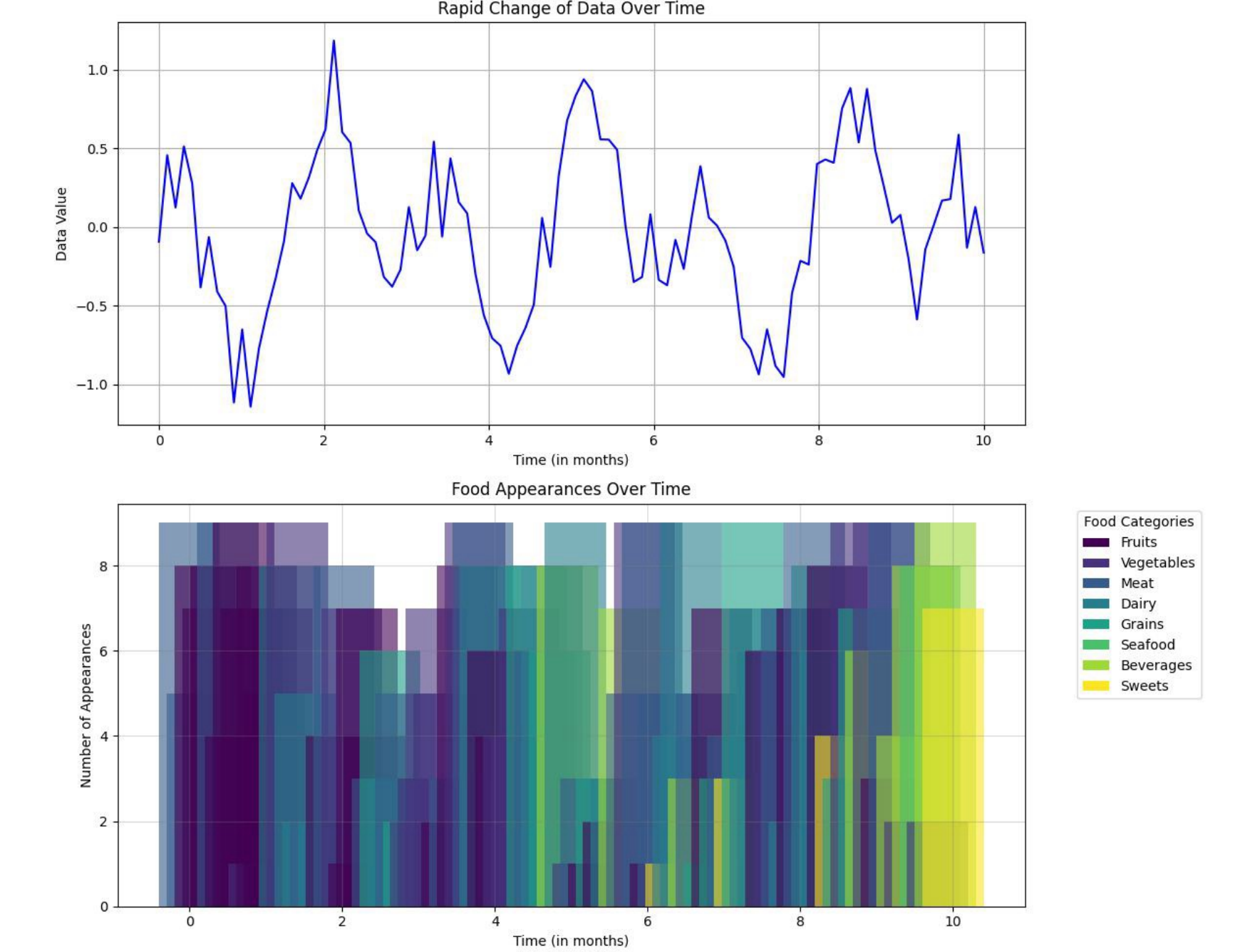


**Objectives:** (a) Continuously changing data stream - no access to old data (b) Remove data appearance constraints (e.g., fixed sample sizes, no repetitions, fixed task sizes)

**Theoretical limit:** Distribution uncertainties in real world scenarios

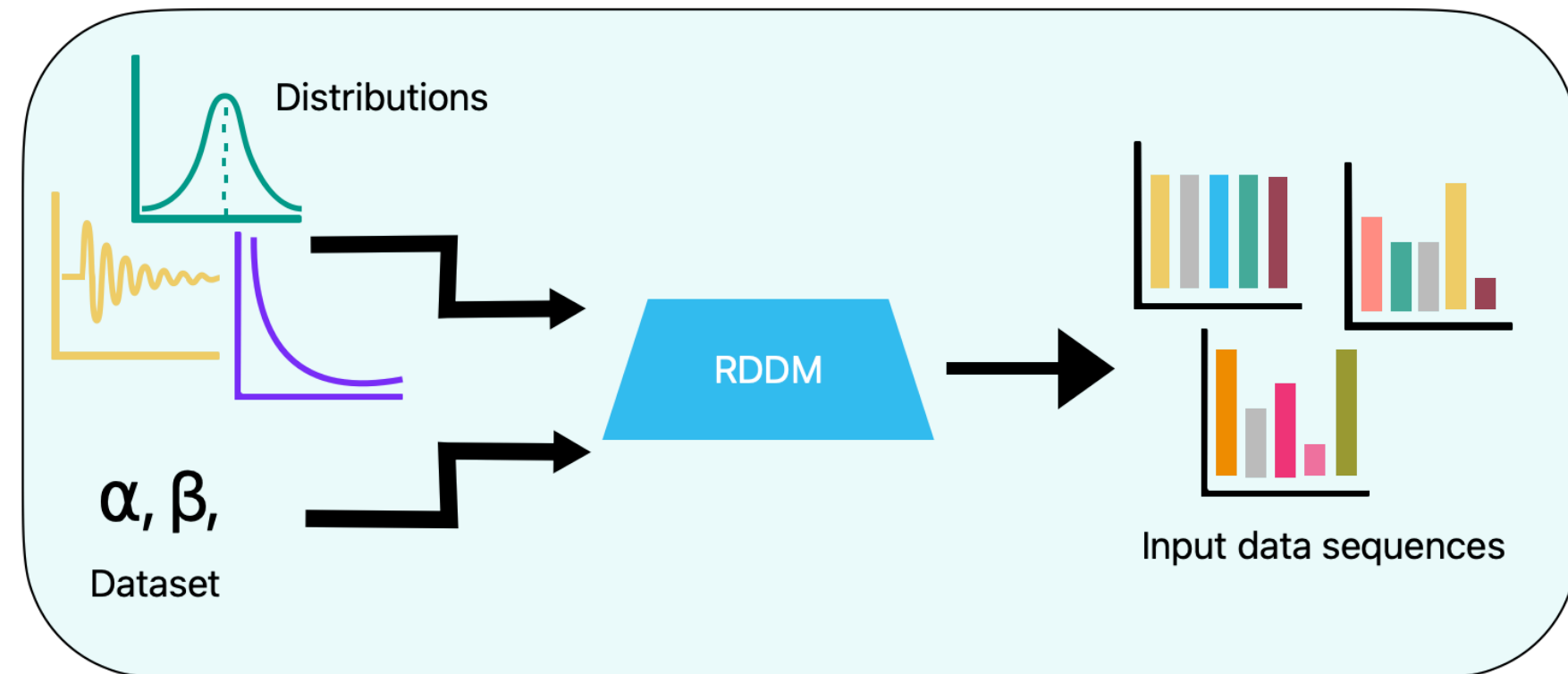
## Real World Food Image Classification

- Rapidly changing data
- Classification models learnt from static datasets – not representative of real-world conditions
- New categories of food introduced over time
- Not practical to re-train models from scratch



## Our method: Realistic Data Distribution Module (RDDM) and Dynamic Model Update (DMU)

### Framework



**Characteristic 2:** Sample sizes (s) of classes in a task, may not be equal.

$$\forall m, n \in N \mid m \neq n$$

$$P(s_{i,m} \neq s_{i,n}) > 0, \forall s_{i,m} \neq s_{i,n} \neq 0$$

**Characteristic 3:** Classes (C) across different tasks could overlap.

$$C_{t_i} \cap C_{t_j} \neq \emptyset \mid t_i \neq t_j$$

Realistic food consumption patterns:

$$K_i^{repeat} = D(i, \alpha)$$

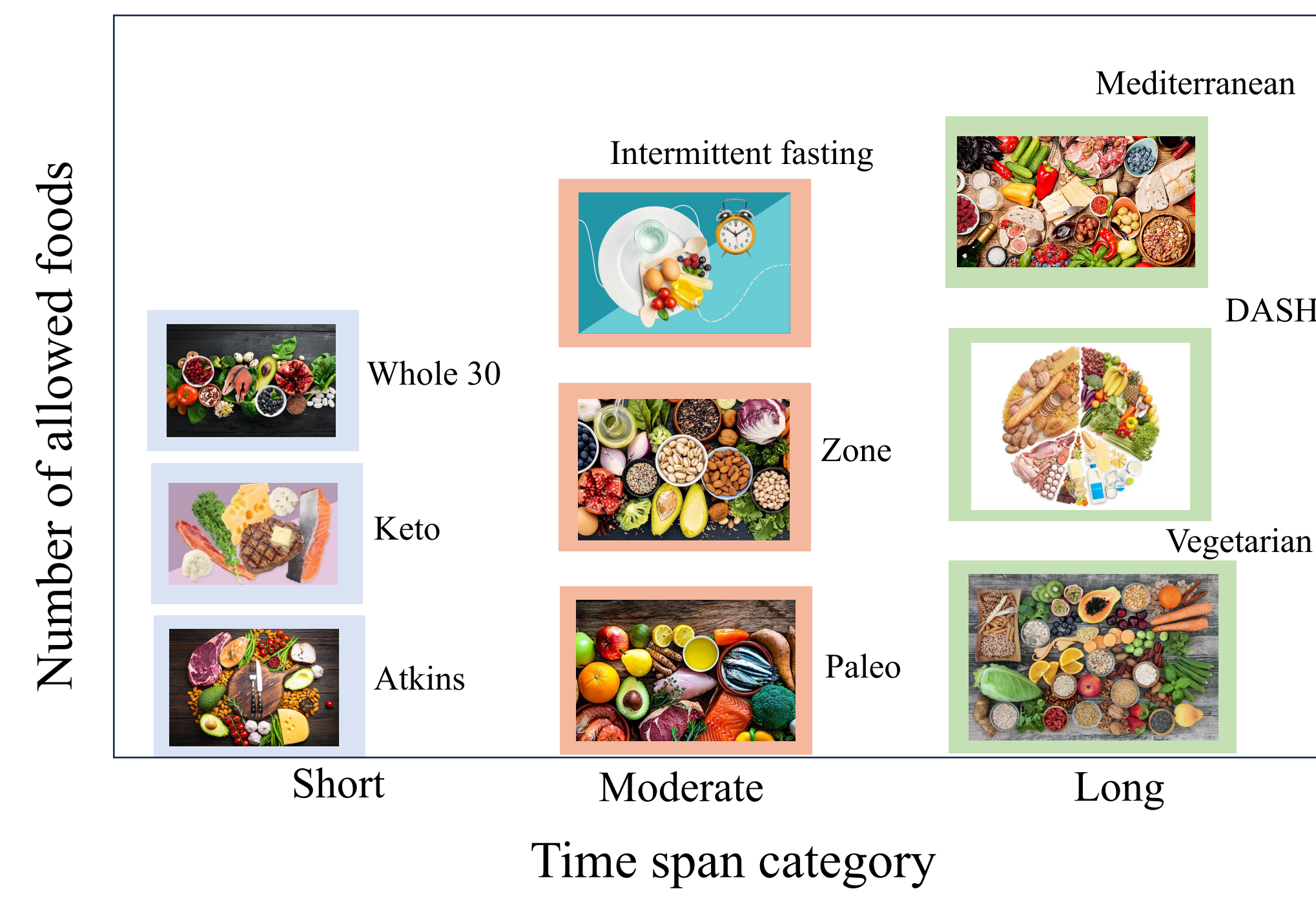
$$K_i^{new} = D(i, \beta)$$

$$K_i = K_i^{repeat} + K_i^{new}$$

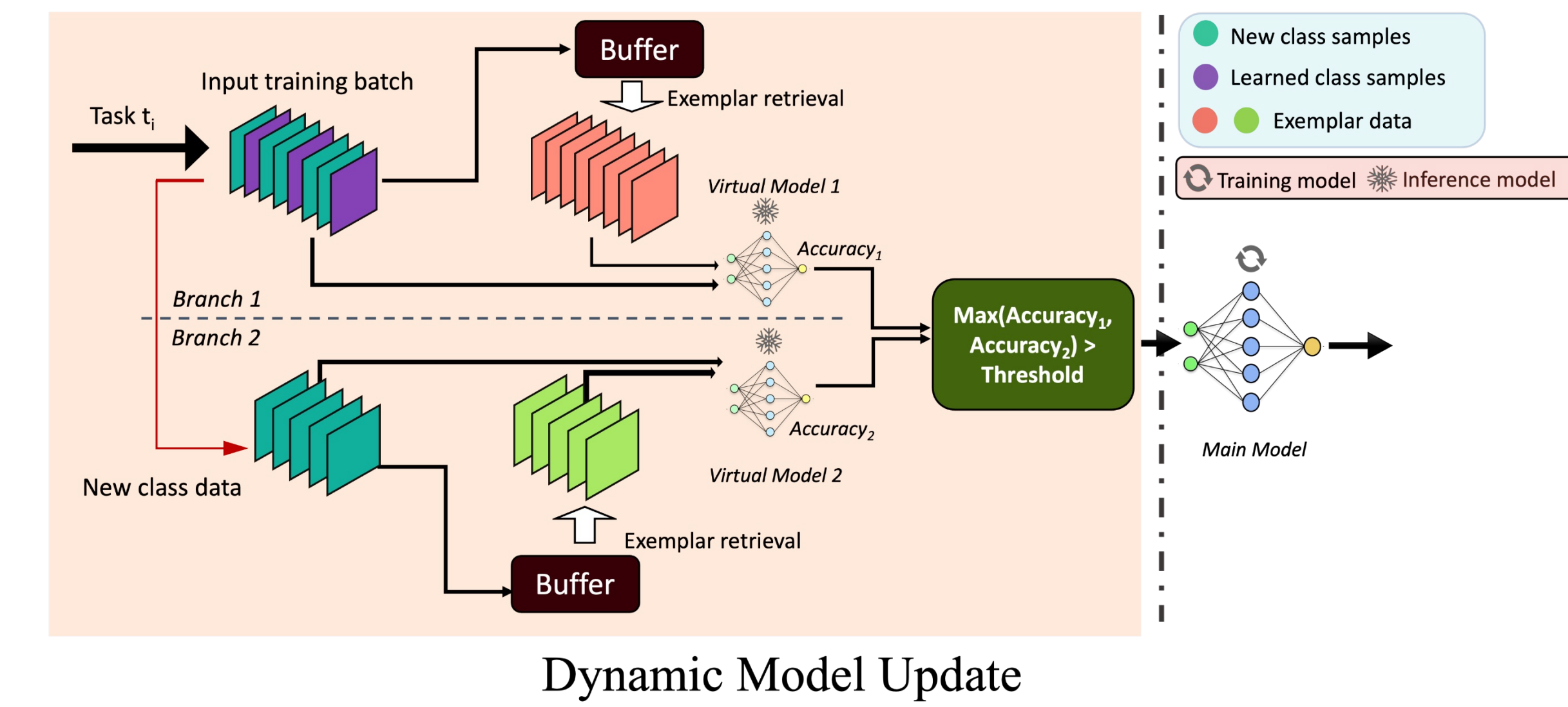
**Characteristic 1:** The total number of classes (K) in any task  $t_i$  is not fixed.

$$K_i = \{i \in C : 1 \leq \sum_j s_{i,j} < N\}$$

### Food Consumption Categories



### Method



- Dynamically handle repetitions to avoid overfitting
- *Attachable* to existing methods

## Experiments

**Datasets:** VFN, Food-101

**Backbone:** ResNet18 (trained from scratch)

**Metrics:** Average Accuracy (%)

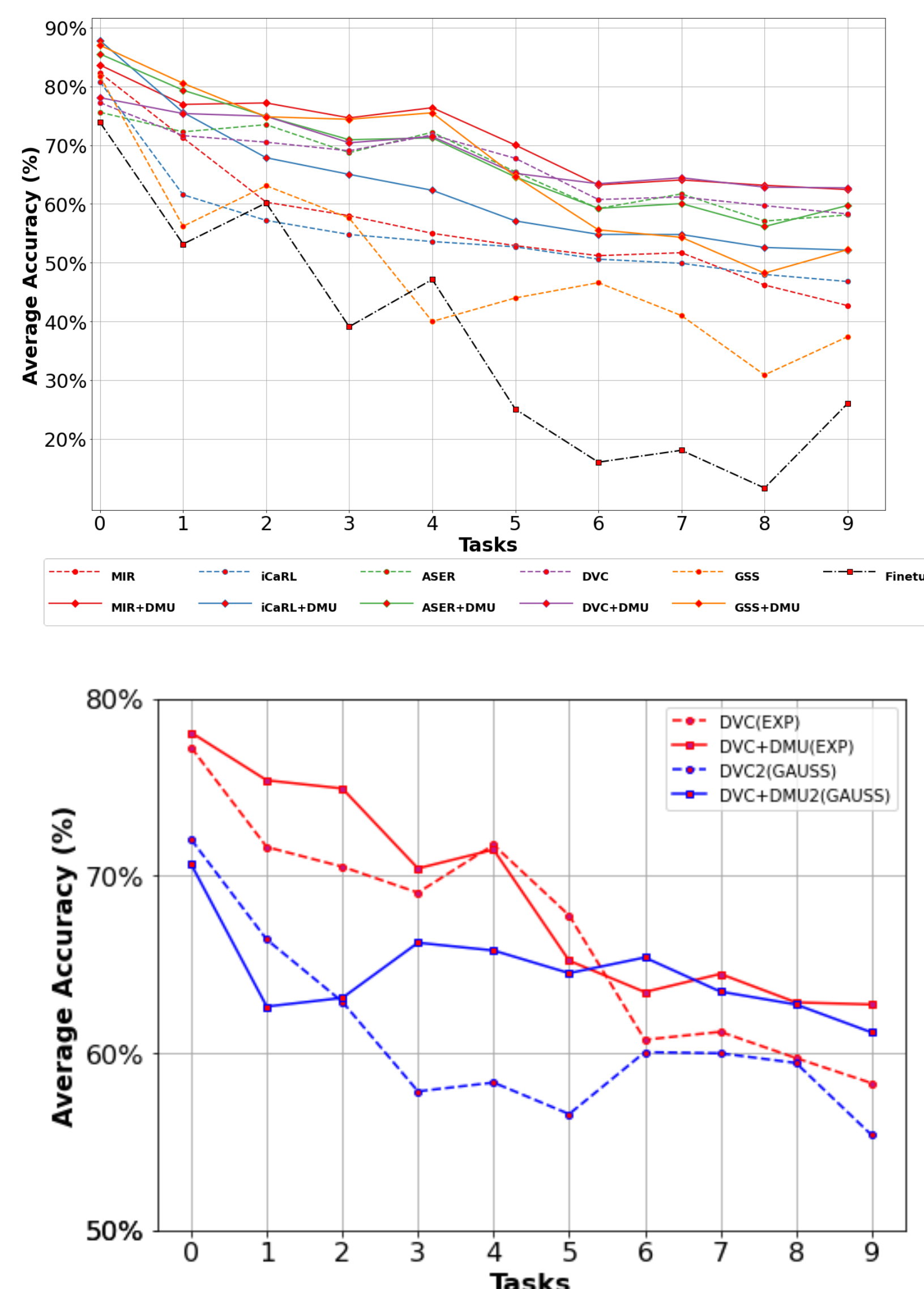
**Distribution:** Gaussian, Exponential

**Task size:** 5, 10, 20

**Food consumption category:** short, medium, long

**Observation:**

1. Existing methods struggle with repetition of data and unequal sample distribution
2. Our method consistently improves performance across task sizes, buffer sizes and distributions.



Dataset	Food-101						VFN					
Task size	5		10		20		5		10		20	
Category	Short	Mod	Long	Short	Mod	Long	Short	Mod	Long	Short	Mod	Long
Finetune	53.00	51.00	48.65	45.23	37.50	35.10	22.00	23.67	21.11	33.10	25.50	26.90
iCaRL [CVPR '17]	75.02	69.34	57.75	67.0	56.6	49.65	57.24	51.69	47.13	59.04	52.01	38.39
iCaRL + DMU	<b>76.04</b>	<b>70.68</b>	<b>59.22</b>	<b>67.14</b>	<b>62.29</b>	<b>52.19</b>	<b>59.72</b>	<b>53.65</b>	<b>50.37</b>	<b>52.72</b>	<b>46.93</b>	<b>36.17</b>
Gain Δ	1.02	1.34	1.47	0.14	5.69	2.54	2.48	1.96	3.24	0.73	1.35	4.56
MIR [NeurIPS '19]	74.71	69.79	57.55	64.0	57.0	48.9	54.15	48.39	43.85	49.41	46.01	43.88
MIR + DMU	<b>82.14</b>	<b>75.69</b>	<b>67.97</b>	<b>72.73</b>	<b>71.17</b>	<b>67.72</b>	<b>65.50</b>	<b>63.03</b>	<b>62.04</b>	<b>54.33</b>	<b>48.06</b>	<b>44.90</b>
Gain Δ	7.43	5.9	10.42	8.73	14.17	18.82	11.35	14.64	18.19	4.92	1.96	1.02
GSS [NeurIPS '19]	72.17	69.77	58.54	51.5	50.5	47.8	40.33	42.8	38.51	53.41	45.64	37.19
GSS + DMU	<b>76.29</b>	<b>74.01</b>	<b>68.19</b>	<b>55.07</b>	<b>66.17</b>	<b>66.06</b>	<b>47.43</b>	<b>49.86</b>	<b>50.13</b>	<b>55.59</b>	<b>47.52</b>	<b>38.83</b>
Gain Δ	4.12	4.24	9.65	3.57	15.67	18.26	4.10	7.06	11.62	2.18	1.88	1.64
ASER [AAAI '21]	77.87	72.51	62.89	67.70	66.6	61.12	59.70	58.29	56.35	51.86	48.56	42.19
ASER + DMU	<b>78.33</b>	<b>73.96</b>	<b>64.06</b>	<b>72.27</b>	<b>68.17</b>	<b>64.06</b>	<b>60.59</b>	<b>59.74</b>	<b>56.08</b>	<b>52.78</b>	<b>51.15</b>	<b>46.08</b>
Gain Δ	0.46	1.45	1.17	4.57	2.1	2.94	0.89	1.45	—	0.92	2.59	3.89
DVC [CVPR '22]	77.06	72.86	64.43	73.46	66.89	61.05	58.74	60.51	59.90	48.55	39.88	38.57
DVC + DMU	<b>78.53</b>	<b>74.96</b>	<b>65.95</b>	<b>74.52</b>	<b>68.75</b>	<b>62.15</b>	<b>60.51</b>	<b>61.82</b>	<b>59.94</b>	<b>50.06</b>	<b>40.63</b>	<b>41.28</b>
Gain Δ	1.47	1.35	1.53	1.06	1.86	1.1	1.77	1.82	0.04	1.51	0.75	2.71

Method	Distribution	Accuracy
DVC	Exp	66.89
DVC+DMU	Exp	<b>68.75</b>
Gain Δ		1.86
DVC	Gauss	60.89
DVC+DMU	Gauss	<b>64.55</b>
Gain Δ		3.75

Average accuracy across different OCIL techniques, along with our module.

Average accuracy across different buffer sizes on VFN dataset, along with our module.

Dataset	VFN					
Buffer size	2K		0.5K			
Task size	20		20			
Category	short	med	long	short	med	long
MIR	30.50	28.93	28.22	27.81	24.72	26.24
MIR + DMU	<b>31.17</b>	<b>30.31</b>	<b>29.63</b>	<b>29.39</b>	<b>27.60</b>	<b>26.33</b>
Gain Δ	0.67	1.38	1.41	1.58	2.88	0.09
ASER	33.29	33.78	29.31	29.21	30.51	27.61
ASER+DMU	<b>33.86</b>	<b>34.70</b>	<b>29.48</b>	<b>29.78</b>	<b>30.92</b>	<b>28.26</b>
Gain Δ	0.57	0.92	0.17	0.57	0.41	0.65
DVC	21.66	20.02	19.00	20.95	19.73	18.80
DVC + DMU	<b>22.70</b>	<b>21.22</b>	<b>18.42</b>	<b>21.08</b>	<b>21.06</b>	<b>19.41</b>
Gain Δ	1.04	1.20	0.58	0.13	1.33	0.61
GSS	27.28	29.32	29.20	22.75	26.47	25.06
GSS + DMU	<b>28.20</b>	<b>32.29</b>	<b>29.22</b>	<b>24.49</b>	<b>30.85</b>	<b>25.98</b>
Gain Δ	0.92	2.97	0.02	1.74	4.38	0.92
iCaRL	42.50	34.00	33.60	36.28	25.60	26.22
iCaRL + DMU	<b>46.34</b>	<b>41.67</b>	<b>45.25</b>	<b>37.74</b>	<b>36.67</b>	<b>39.04</b>
Gain Δ	3.84	7.67	11.65	1.46	11.07	12.82

### Contribution and Future Work

We introduce a novel Realistic Data Distribution Module (RDDM) to simulate real-world food consumption patterns, along with a pluggable Dynamic Model Update (DMU) module setting a benchmark for Online Class Incremental Learning, particularly in real-world situations. This takes us a step closer towards achieving lifelong learning in real-world food image classification.

**Our Code is open source!**

**Scan the QR code to check our paper and code**

