Improving the Separability of a Reservoir Facilitates Learning Transfer

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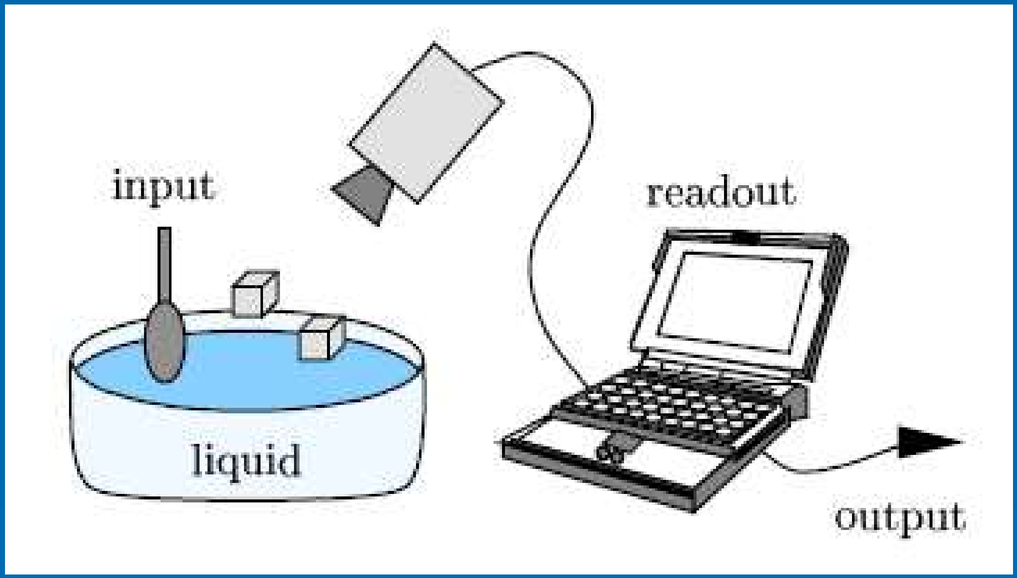
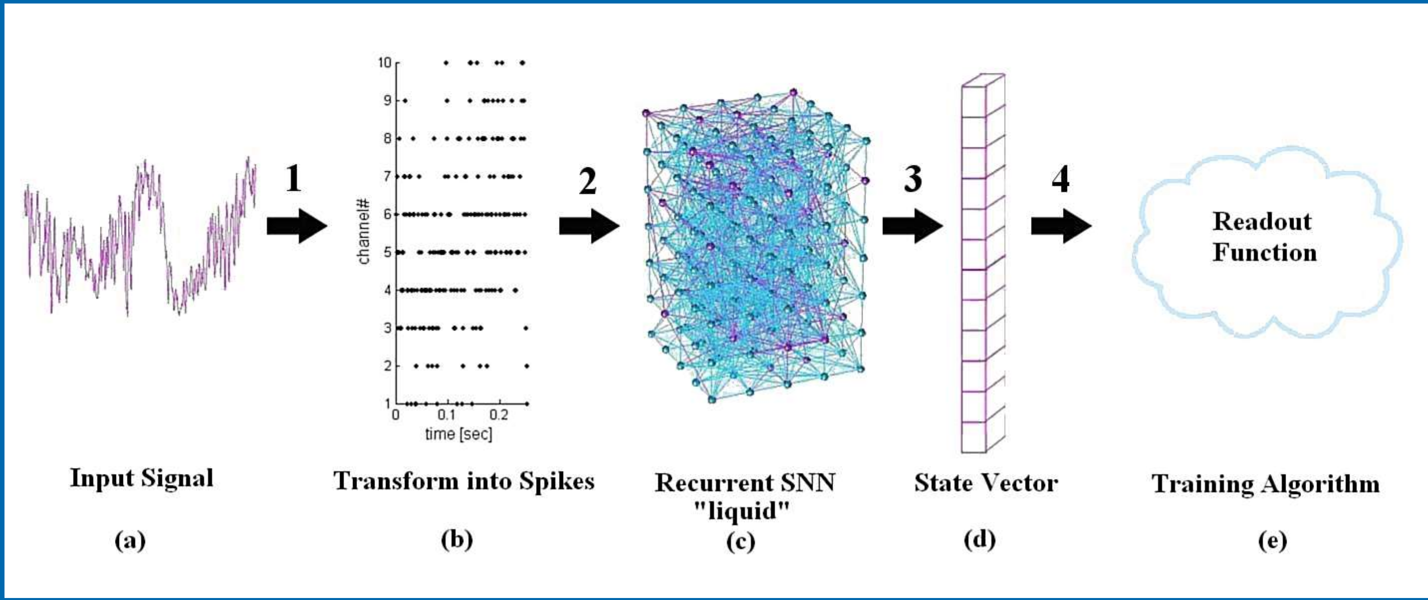
Liquid State Machine



A type of reservoir computing utilizing a recurrent spiking neural network (SNN) as the reservoir (liquid).

Liquid State Machine



1. Input is transformed into a series of spikes.
2. These spikes are introduced into the liquid.
3. Snap-shots of the liquid's state are taken (state vector).
4. State vectors are introduced as input into the readout function.

Properties of LSMs

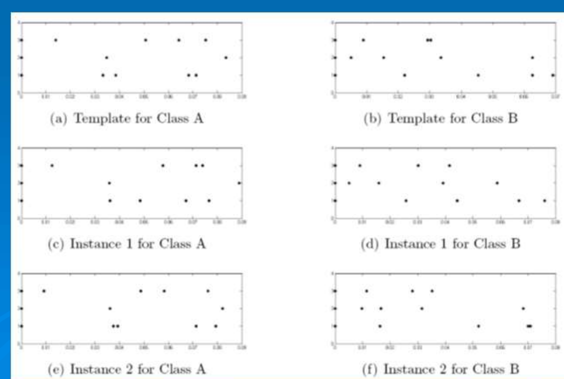
- Exploit power of recurrent spiking neural networks
- Random reservoir creation; typically no training of the reservoir
- Requires the creation of at least hundreds of liquids for acceptable results
- When an acceptable reservoir is found, it often can transfer to different problems well
- Acceptable reservoirs work by "effectively separating" different classes of input

Classification Problems

- Frequency Recognition
  - 4 input neurons
  - 5 classes
  - Identify different combinations of *slow* and *fast* input neurons

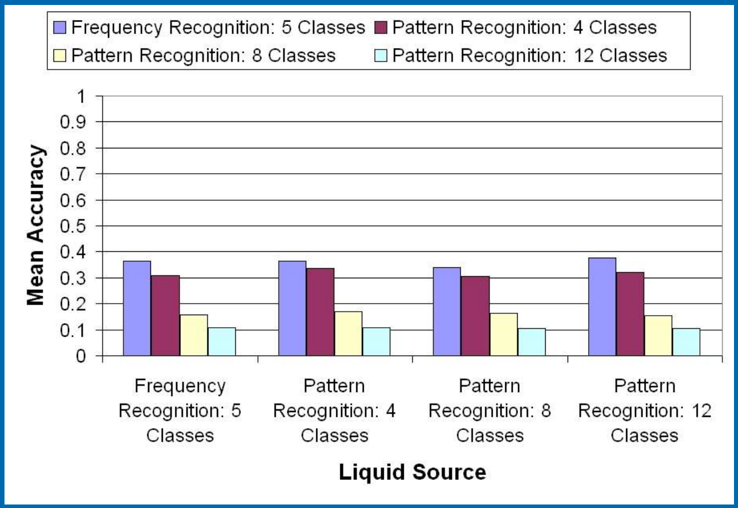
	Input 1	Input 2	Input 3	Input 4
Class 1	1	0	0	0
Class 2	0	1	0	0
Class 3	1	1	0	0
Class 4	0	0	1	0
Class 5	1	0	1	0

- Pattern Recognition
  - 8 input neurons
  - 4, 8, and 12 classes
  - Identify different spiking patterns based on templates

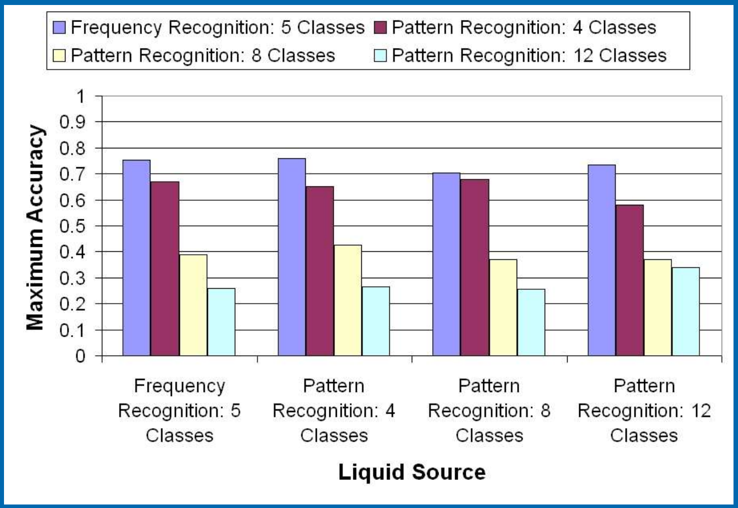


(a) Template for Class A
(b) Template for Class B
(c) Instance 1 for Class A
(d) Instance 1 for Class B
(e) Instance 2 for Class A
(f) Instance 2 for Class B

Learning Transfer with Traditional LSMs



Mean Accuracy

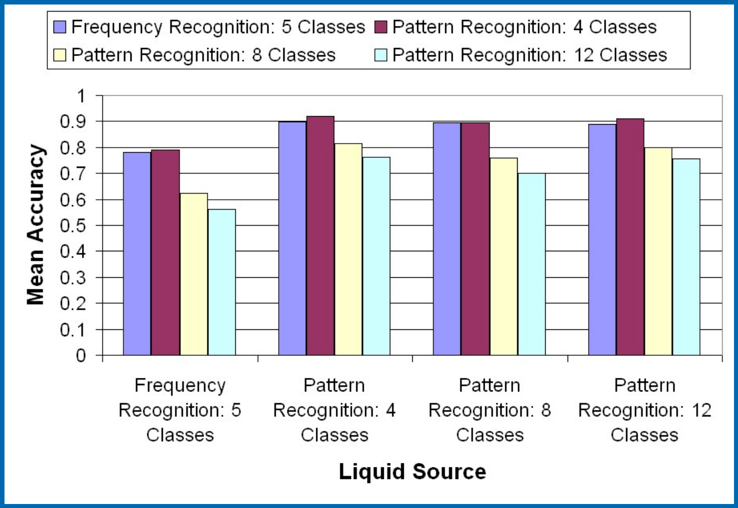


Maximum Accuracy

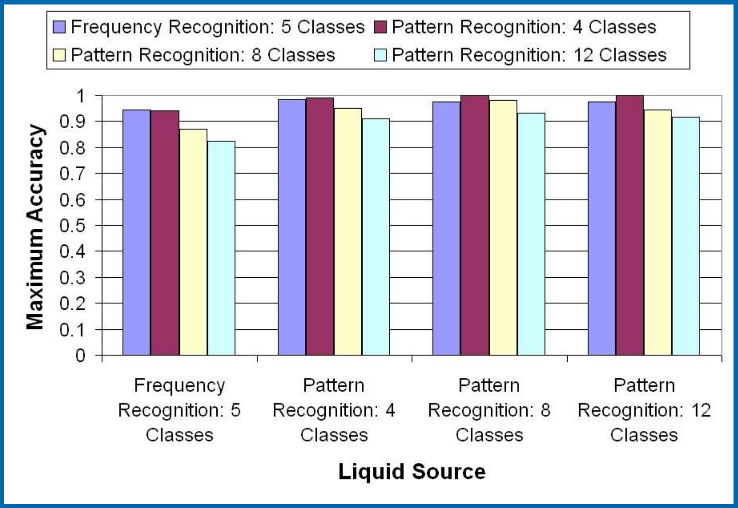
Training the Reservoir

- Randomly create a reservoir in the traditional sense
- Adjust the architecture of the reservoir until it can "effectively separate"
- Training is driven by separation property rather than error

Learning Transfer after Reservoir Training



Mean Accuracy



Maximum Accuracy

Separation

$$Sep_{\Psi}(O(t)) = \frac{C_d(t)}{C_v(t) + 1}$$

Inter-class distance:

$$C_d(t) = \sum_{m=1}^{N} \sum_{n=1}^{N} \frac{\|\mu(O_m(t)) - \mu(O_n(t))\|_2}{N^2}$$

Intra-class variance:

$$C_v(t) = \frac{1}{N} \sum_{m=1}^{N} \rho(O_m(t))$$

Separation

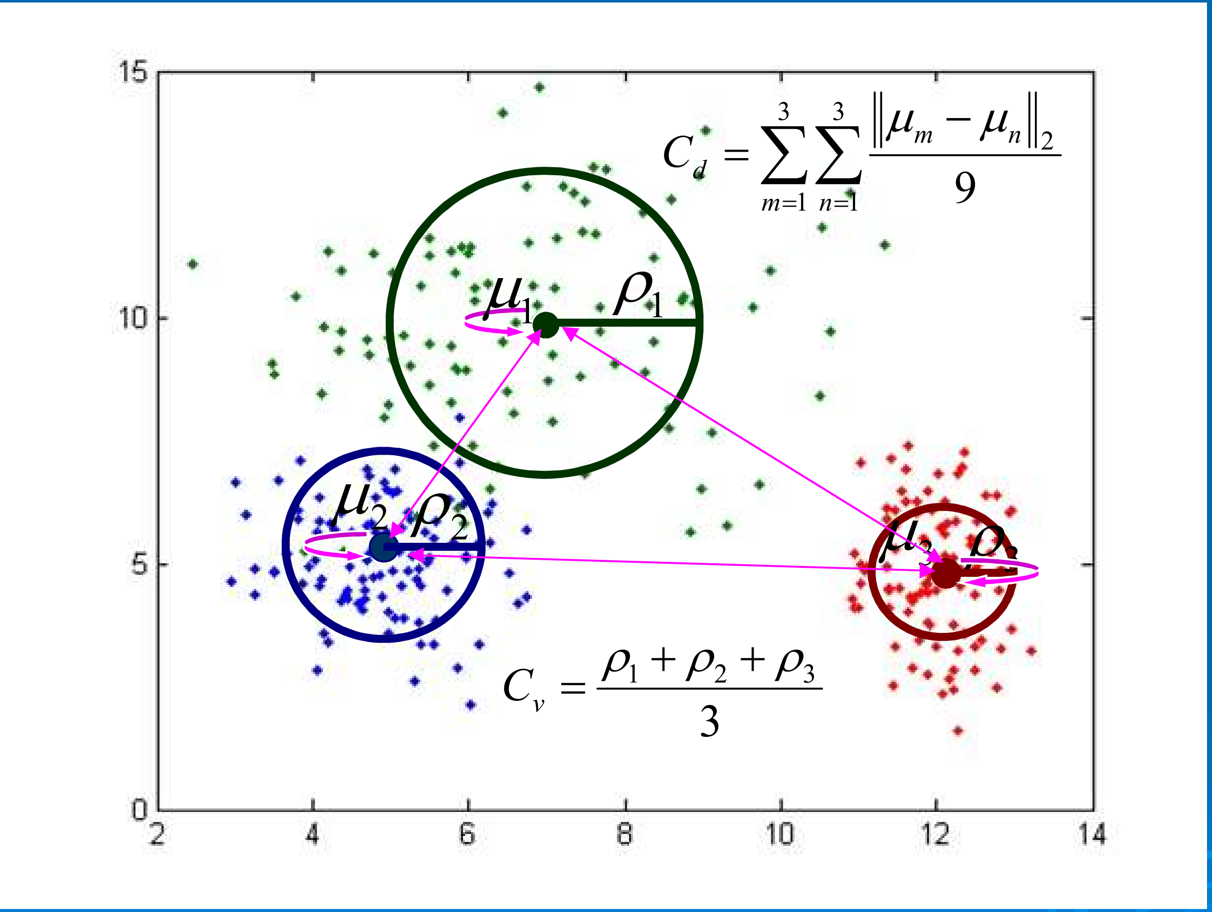
Center of mass for class *m*:

$$\mu(O_m(t)) = \frac{\sum_{o_n \in O_m(t)} o_n}{|O_m(t)|}$$

Average variance within class *m*:

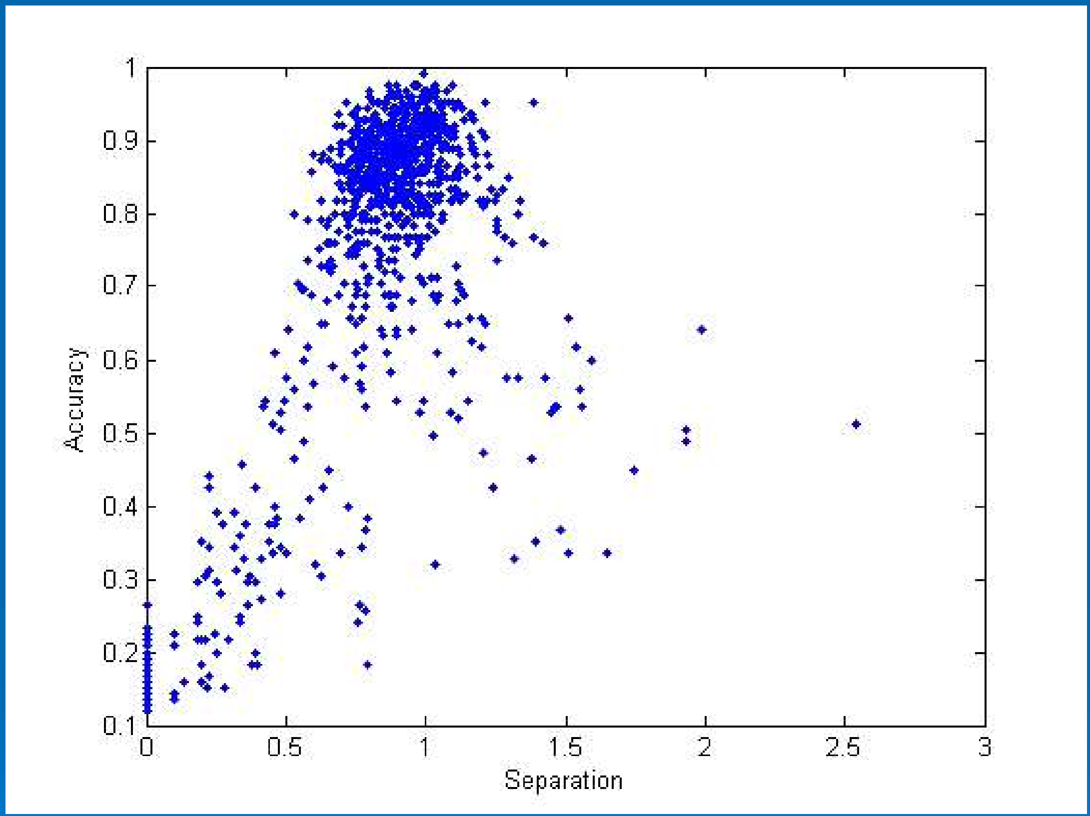
$$\rho(O_m(t)) = \frac{\sum_{o_n \in O_m(t)} \|\mu(O_m(t)) - o_n\|_2}{|O_m(t)|}$$

Separation



$$Sep_{\Psi}(O(t)) = \frac{C_d(t)}{C_v(t)+1}$$

Separation



Correlation coefficient is 0.6876

Separation Driven Synaptic Modification (SDSM)

- Problems with liquids
  1. Too little distance between centers of mass
  2. Too much variance within classes

- Solutions
  1. Strengthen weak synapses, weaken strong synapses
  2. Strengthen strong synapses, weaken weak synapses

- Chaos
  1. Increase chaos in liquid
  2. Decrease chaos in liquid

SDSM

Weight update:

$$w_{ij}(t+\Delta t) = sgn(w_{ij}(t))(|w_{ij}(t)| + E(t)\lambda F(t))$$

Effect of separation:

$$E(t) = R_s\,(v_i - d_i)$$

Relative synaptic strength:

$$R_s = \frac{|w_{ij}(t)| - \mu_w}{M_w}$$

SDSM

Differentiating classes of input (increase chaos):

$$d_i = \alpha_i \left(1 - \frac{C_d}{Sep^*_\Psi}\right)$$

Activity of Neuron *i*:

$$\alpha_i = \frac{\sum_{k=1}^{N} \mu_i(O_k(t))}{N}$$

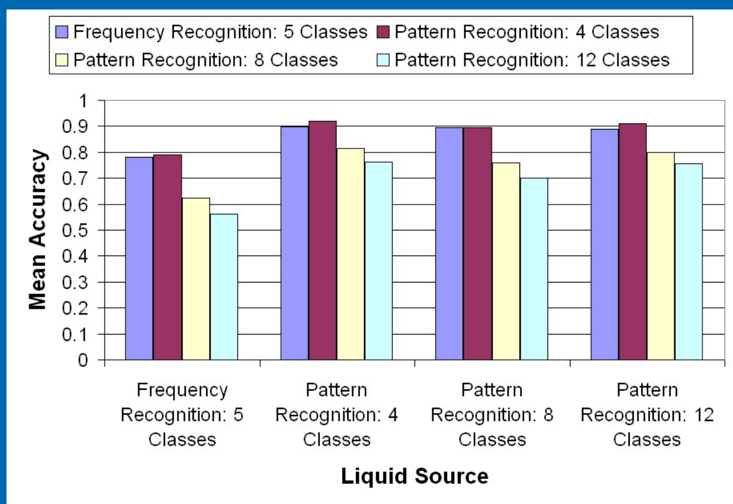
$$C_v(t) = \frac{1}{N} \sum_{m=1}^{N} \rho(O_m(t))$$

Decreasing variance within classes (decrease chaos):

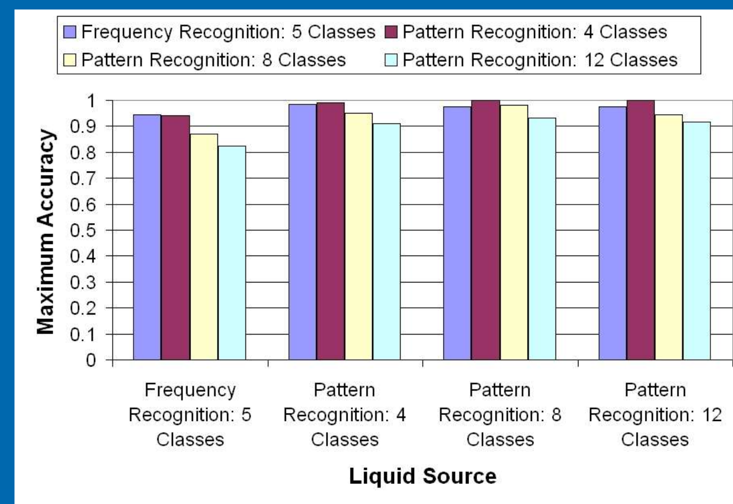
$$v_i = \frac{\sum_{k=1}^{N} \mu_i(O_k(t))\rho(O_k(t))}{N}$$

Compare

Learning Transfer with SDSM

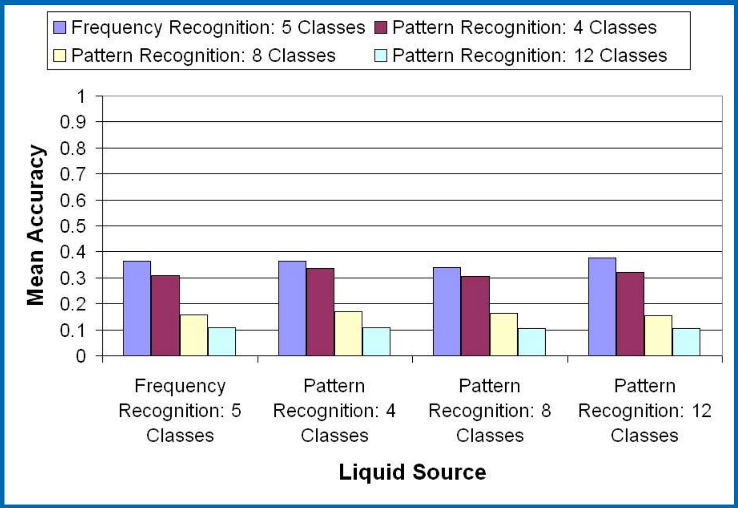


Mean Accuracy

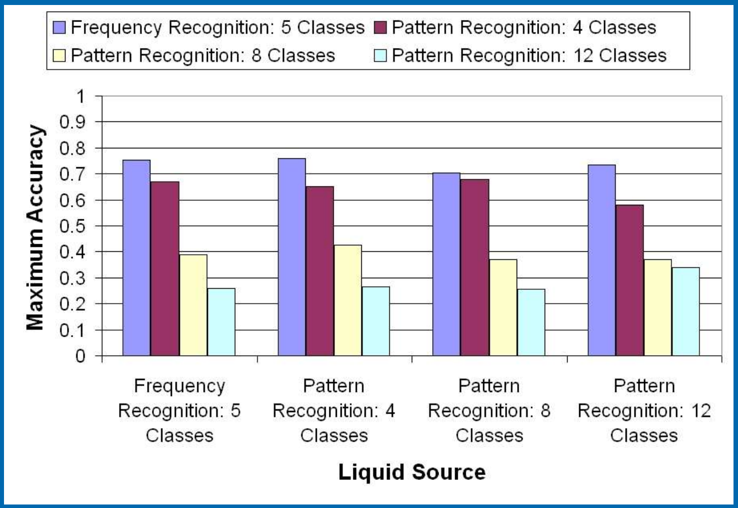


Maximum Accuracy

Learning Transfer with Traditional LSMs



Mean Accuracy



Maximum Accuracy

Conclusions

- The reservoir in a LSM can be used effectively on different problems
- SDSM successfully trains a reservoir without compromising this ability of the reservoir
- SDSM exhibits learning transfer
  - Differing numbers of classes
  - Naïve translation from one input representation into another

Future Work

- Compare a greater number problems with greater diversity
- Experiment with alternative "reservoir-quality-assessing" metrics such as statistical complexity
- Provide a large spectrum of training data (from a variety of problems) to train a single reservoir

Questions