

# ArchData

## 技术峰会北京站

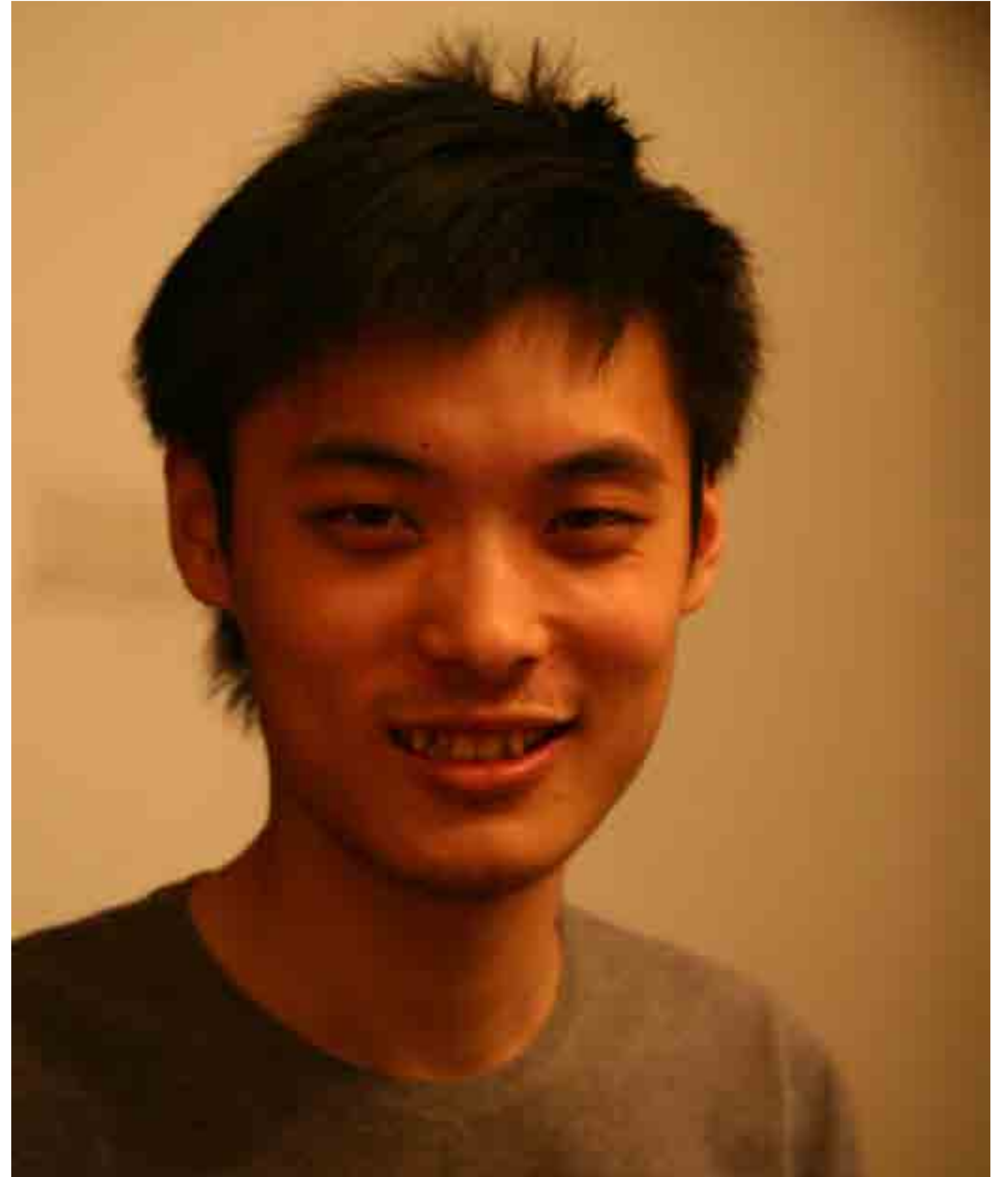
主办方： 中生代技术  
FRESHMAN TECHNOLOGY  快CTO

2017年9月24日北京海淀区丹棱街5号微软亚太研发中心一号楼一层 故宫会议室



# ThoughtWorks

杨博





ThoughtWorks®

# 神经网络与函数式编程

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*By 杨博 at ThoughtWorks*





# DeepLearning.scala

可微分式编程

函数式编程

动态神经网络

插件



# TO DEFINE NEURO NETWORK

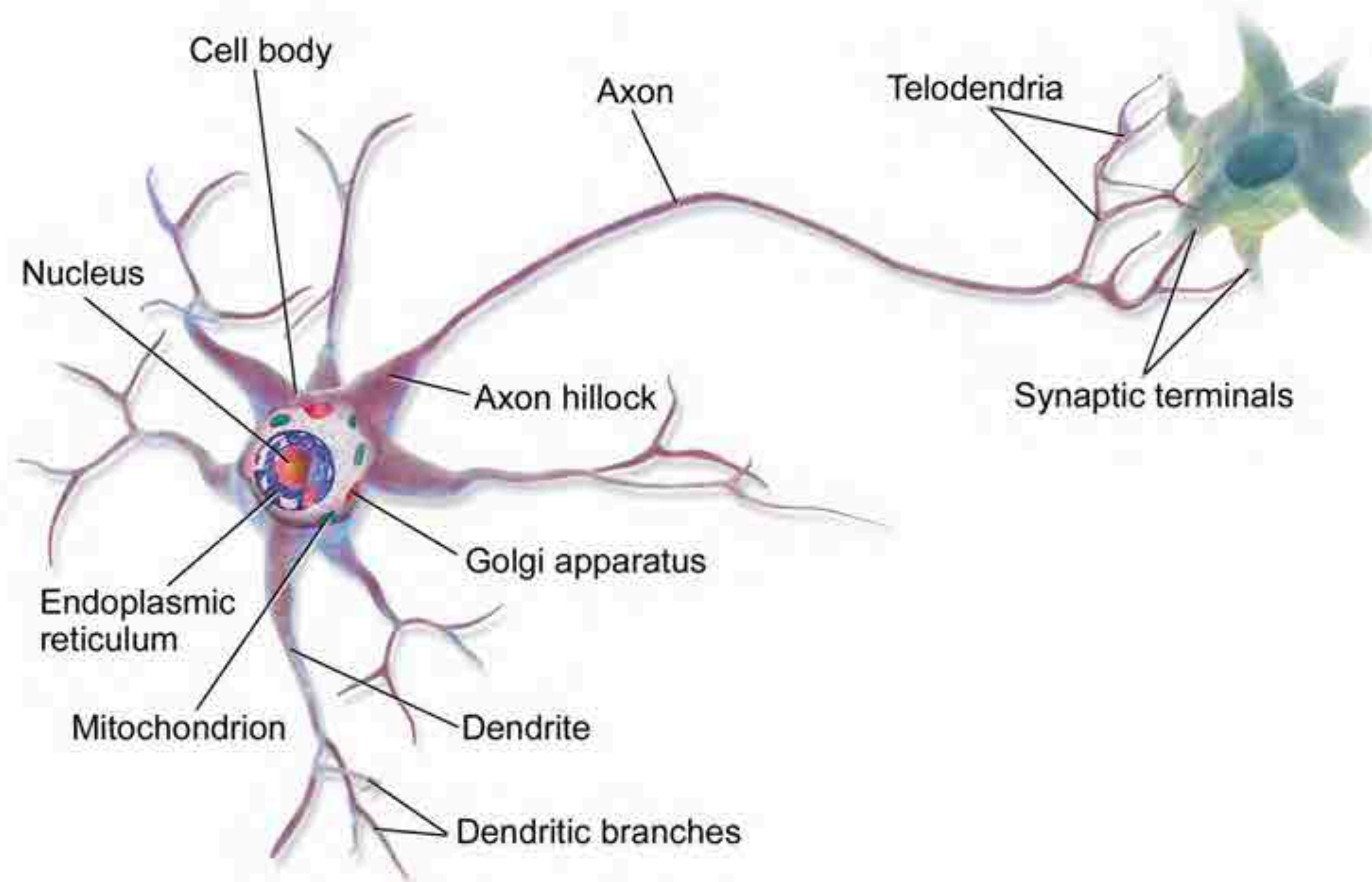
---

*we have done ...*

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# BIOLOGICAL?

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# FEATURE ENGINEERING?

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# NEURO NETWORK IS FUNCTIONAL PROGRAMMING

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*we have done ...*



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# IQ TEST ROBOT

---

What is the next number in the sequence?

3,4,5,?

13,19,25,?

---

# THE SIGNATURE OF IQ TEST ROBOT

---

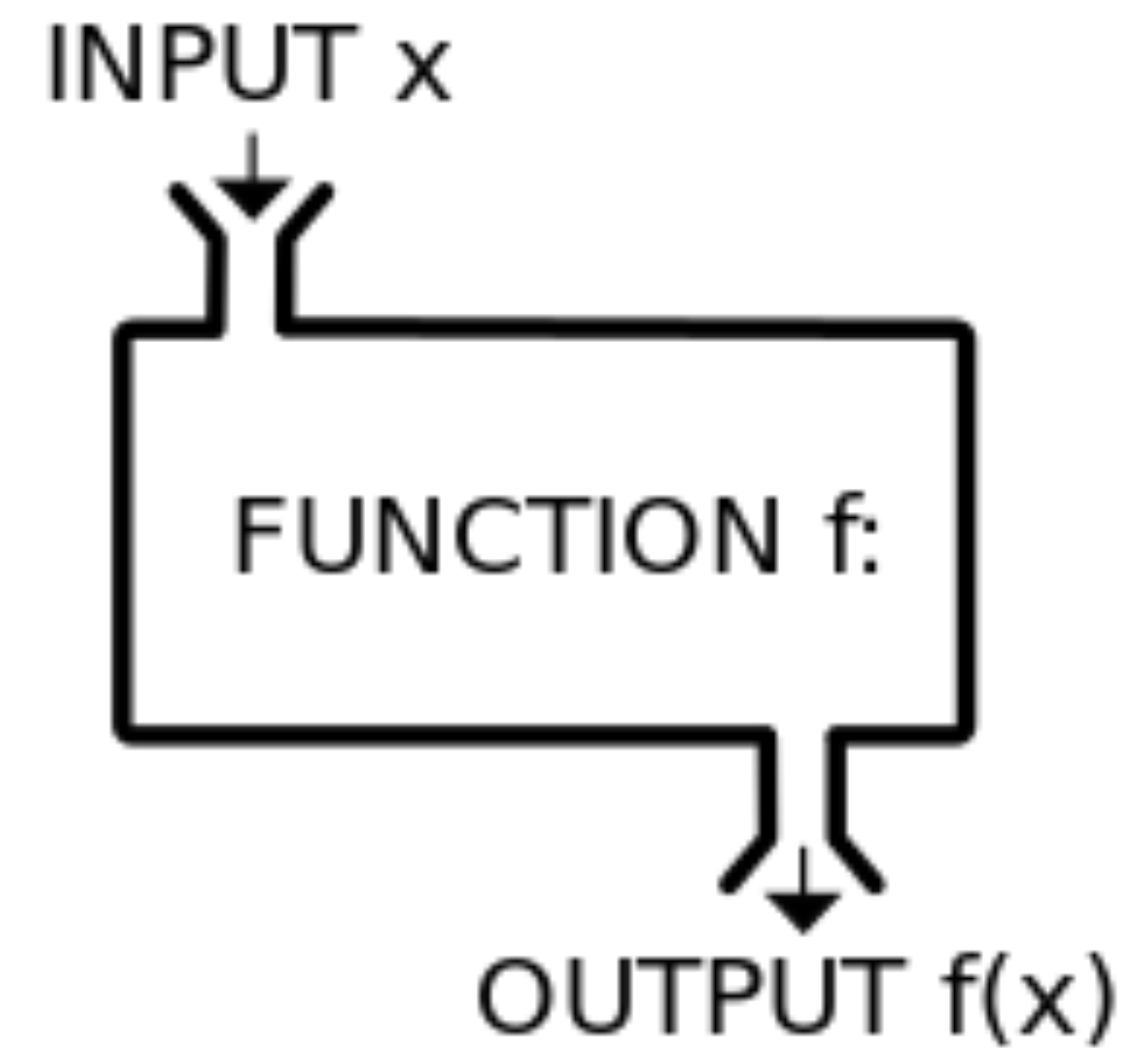
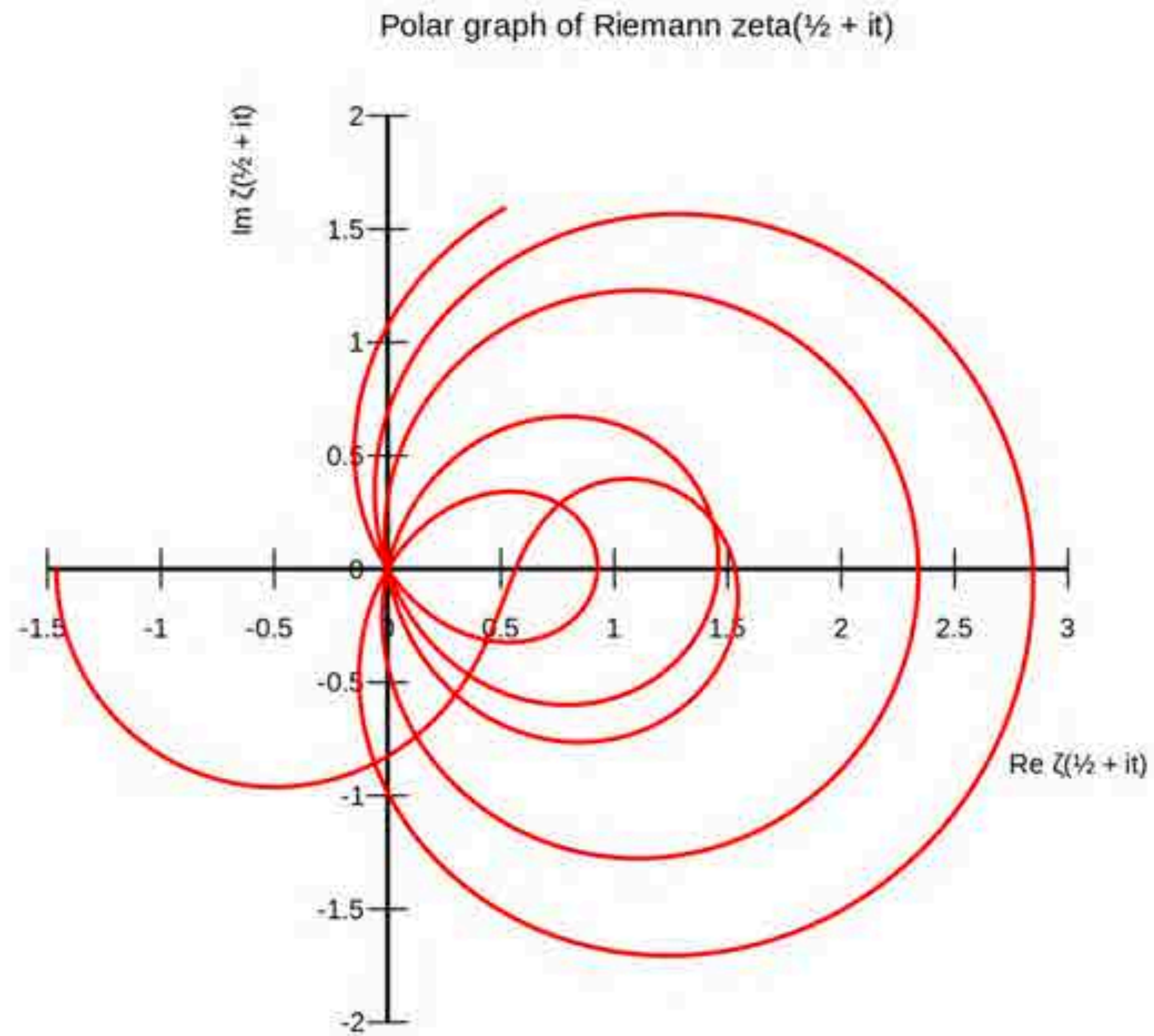
```
def guessNextNumber(question: Seq[Double]): DoubleLayer = ???
```

```
println(guessNextNumber(Seq(3, 4, 5)).predict.blockingAwait)
```

```
println(guessNextNumber(Seq(13, 19, 25)).predict.blockingAwait)
```



# FUNCTION?



---

# TRAINING THE IQ TEST ROBOT

---

```
def lossFunction(robotAnswer: DoubleLayer, expectedAnswer: Double): DoubleLayer = ???
```

```
def iqTestRobotTrainer(question: Seq[Double], expectedAnswer: Double): DoubleLayer = {  
  val robotAnswer = guessNextNumber(question)  
  lossFunction(robotAnswer, expectedAnswer)  
}
```

```
iqTestRobotTrainer(Seq(3, 4, 5), 6).train.blockingAwait  
iqTestRobotTrainer(Seq(13, 19, 25), 31).train.blockingAwait
```



---

# THE STRUCTURE OF THE IQ TEST ROBOT

---

// 惰性初始化的权重列表

```
val weights: Stream[DoubleWeight] = Stream.continually(DoubleWeight(math.random))
```

// 用map/reduce编写的多项式加法预测函数

```
def guessNextNumber(question: Seq[Double]): DoubleLayer = {  
  (question zip weights).map {  
    case (element, weight) => element * weight  
  }.reduce(_ + _)  
}
```

// 平方惩罚函数

```
def lossFunction(robotAnswer: DoubleLayer, expectedAnswer: Double): DoubleLayer = {  
  val difference: DoubleLayer = robotAnswer - expectedAnswer  
  difference * difference  
}
```

# META-PROGRAMMING

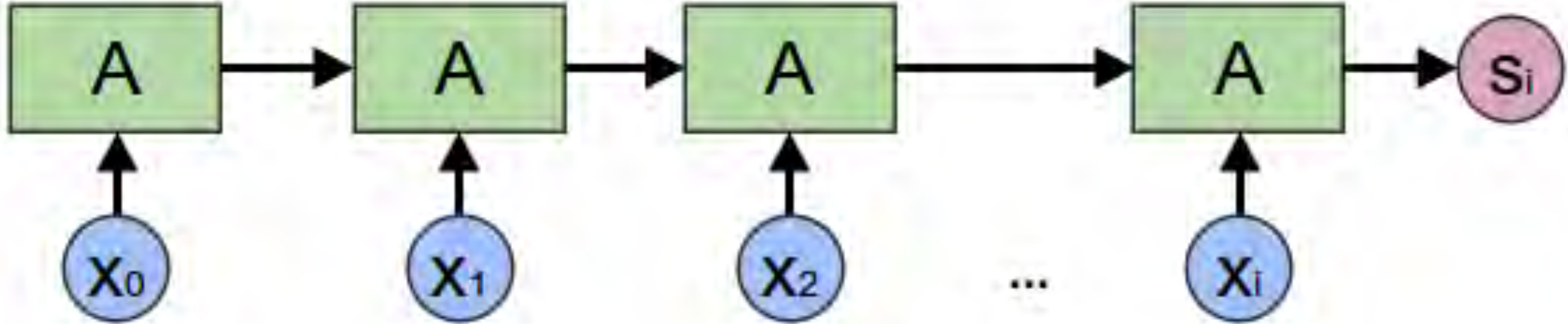




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# ENCODING RECURRENT NEURAL NETWORKS

---



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# ENCODING RECURRENT NEURAL NETWORKS

---

```
package scala.collection
trait Seq[A] {
  def foldLeft[B](z: B)(step: (B, A) => B): B
}
```



---

# ENCODING RECURRENT NEURAL NETWORKS

---

```
type Input = Seq[DoubleLayer]
type State = Seq[DoubleLayer]
```

```
def step(hiddenState: State, xi: Input): State = ???
```

```
def encodingRNN(x: Seq[Input]): State = {
  val initialState: State = Seq.empty[DoubleLayer]
  x.foldLeft(initialState)(step)
}
```

---

# ENCODING RECURRENT NEURAL NETWORKS

---

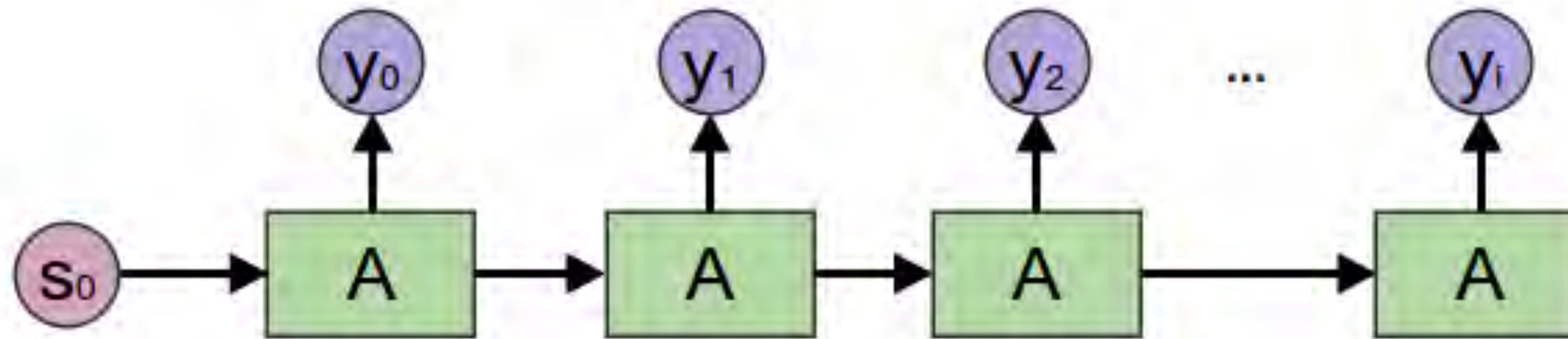
```
val NumberOfOutputFeatures = 10
```

```
val weight: Seq[Seq[DoubleWeight]] = Seq.fill(NumberOfOutputFeatures)(  
  Stream.continually(DoubleWeight(math.random))  
)
```

```
def step(hiddenState: State, xi: Input): State = {  
  tanh(matrixMultiply(hiddenState ++ xi, weight))  
}
```



# GENERATING RECURRENT NEURAL NETWORKS



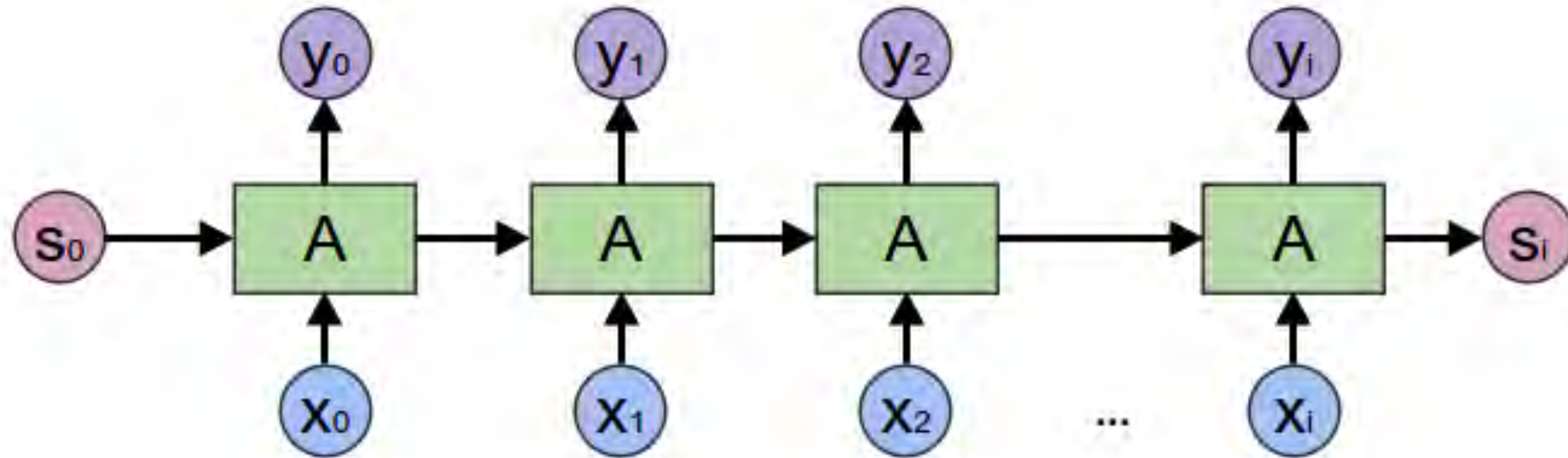
```
package scalaz
object DList {
  def unfoldr[A, B](b: B, f: B => Option[(A, B)]): DList[A]
}
```

```
type State = Seq[DoubleLayer]
type Output = Seq[DoubleLayer]

def step(hiddenState: State): Option[(State, Output)] = ???

def generatingRnn(seed: State): DList[Output] = {
  DList.unfoldr(seed)(step)
}
```

# GENERAL RECURRENT NEURAL NETWORKS



```
package scalaz
class IList[A] {
  def mapAccumLeft[B, C](c: C)(f: (C, A) => (C, B)): (C, IList[B])
  def mapAccumRight[B, C](c: C)(f: (C, A) => (C, B)): (C, IList[B])
}
```

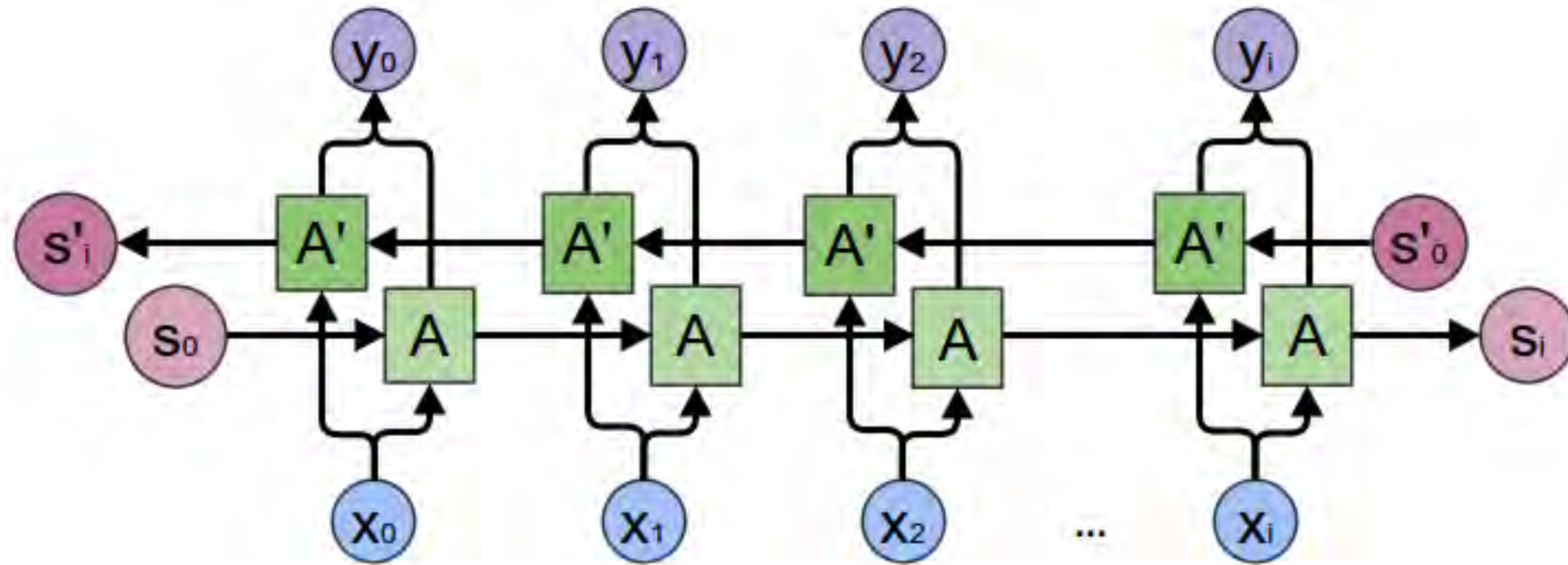
```
type State = Seq[DoubleLayer]
type Input = Seq[DoubleLayer]
type Output = Seq[DoubleLayer]

def step(hiddenState: State, xi: Input): (State, Output) = ???

def rnn(x: IList[Input], seed: State): (State, IList[Output]) = {
  x.mapAccumLeft(seed)(step)
}
```



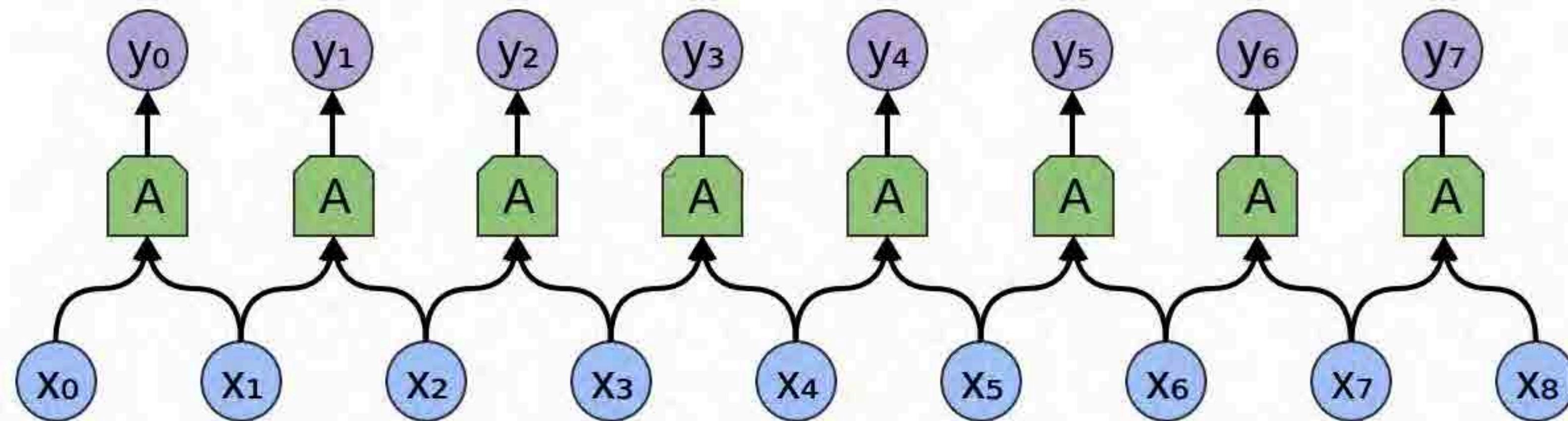
# BIDIRECTIONAL RECURSIVE NEURAL NETWORKS



```
def leftStep(hiddenState: State, xi: Input): (State, Output) = ???  
def rightStep(hiddenState: State, xi: Input): (State, Output) = ???
```

```
def bidirectionalRnn(x: IList[Input], leftSeed: State, rightSeed: State): IList[Output] = {  
  val (_, leftToRight) = x.mapAccumLeft(leftSeed)(leftStep)  
  val (_, rightToLeft) = x.mapAccumRight(rightSeed)(rightStep)  
  leftToRight.zip(rightToLeft).map { pair =>  
    pair._1 ++ pair._2  
  }  
}
```

# CONVOLUTIONAL NEURAL NETWORKS



```
package scala.collection.immutable
class List {
  def map[B](f: A => B): List[B]
  def zip[B](that: List[B]): List[(A, B)]
}
```

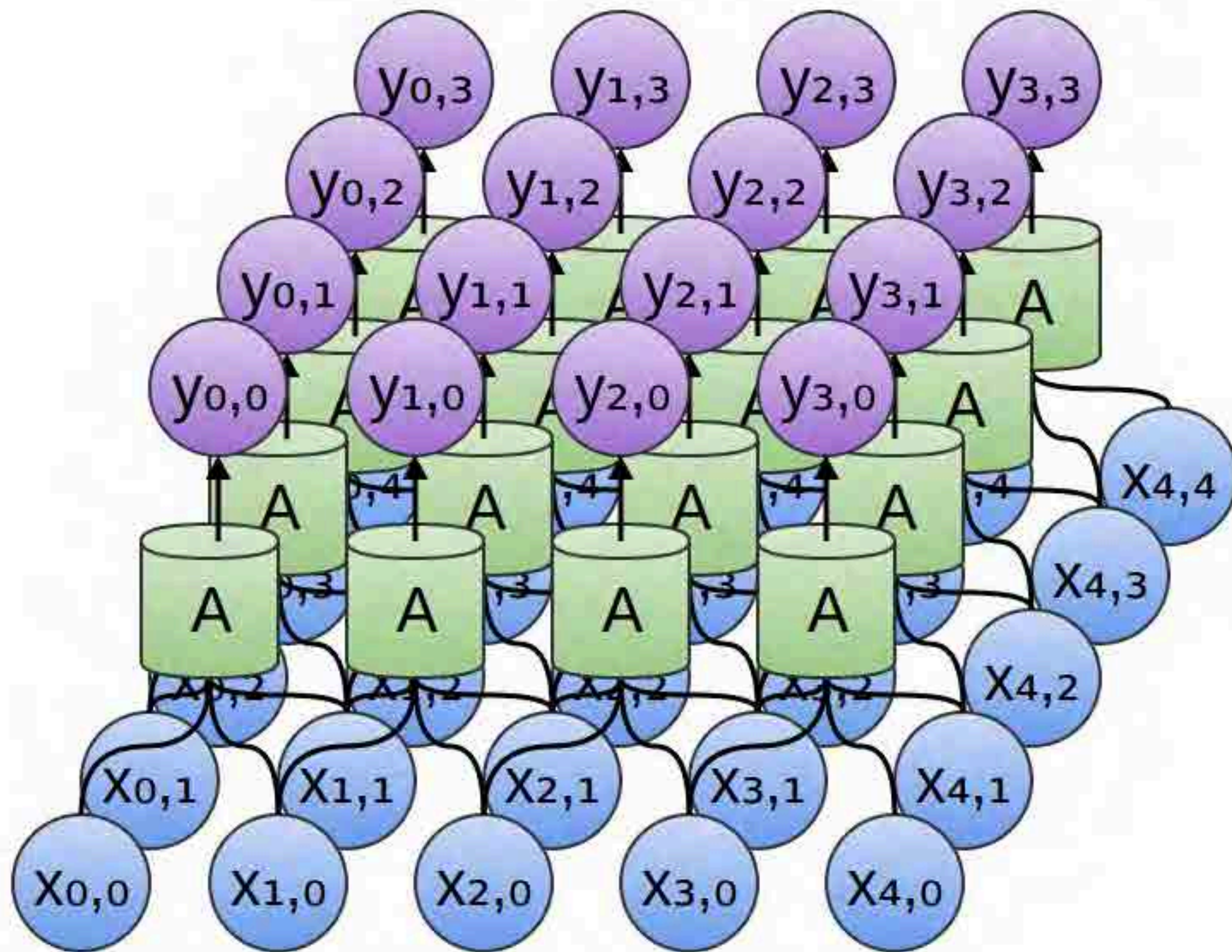
```
type Input = Seq[DoubleLayer]
type Output = Seq[DoubleLayer]

def kernel1x2(xi: Input, xj: Input): Output

def cnn1d(x: List[Input]): List[Output] = {
  x.zip(x.tail).map(kernel)
}
```



# TWO DIMENSIONAL CONVOLUTIONAL NETWORK



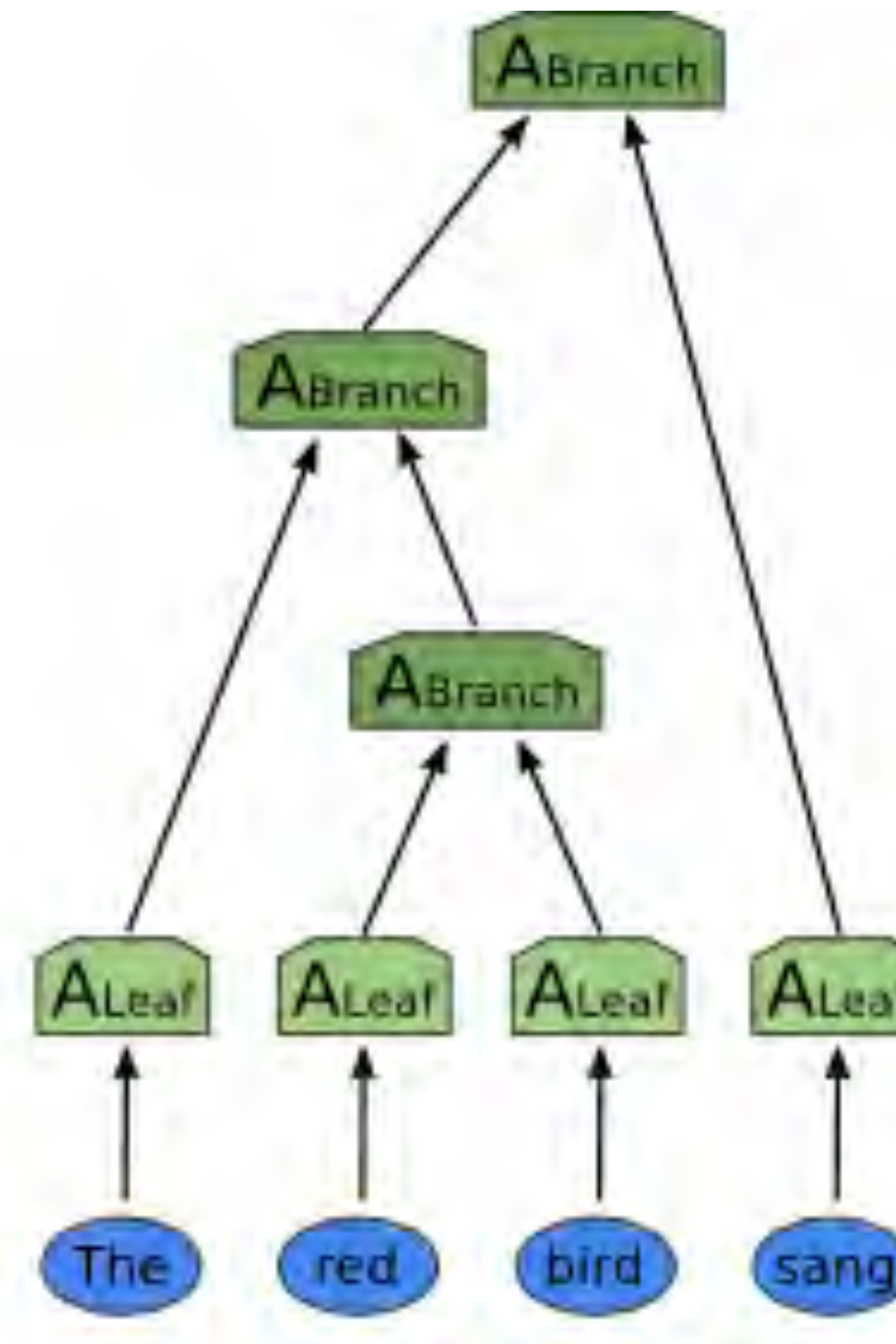
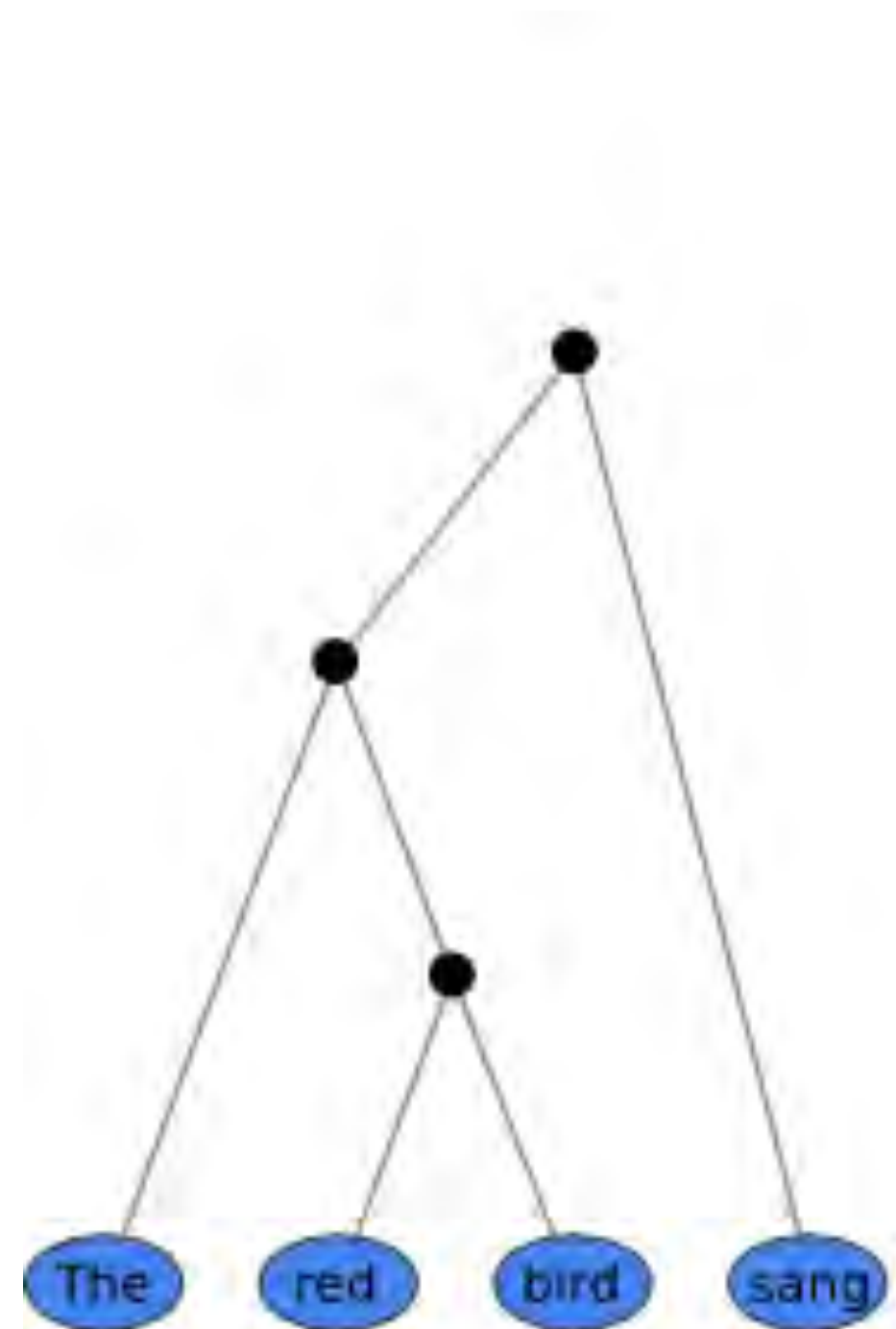
```
type Input = Seq[DoubleLayer]
type Output = Seq[DoubleLayer]

def kernel2x2(xi: Input, xj: Input, xk: Input, xl: Input): Output

def cnn2d(x: List[List[Input]]): List[Output] = {
  val x00 = x
  val x01 = x.map(_.tail)
  val x10 = x.tail
  val x11 = x.tail.map(_.tail)
  (x zip x01 zip x10 zip x11).map {
    case ((xi, xj), xk), xl => kernel2x2(xi, xj, xk, xl)
  }
}
```



# RECURSIVE NEURAL NETWORKS



```
package scalaz
class Tree {
  def scanr[B](g: (A, Stream[Tree[B]]) => B): Tree[B]
}
```

```
type Input = Seq[DoubleLayer]
type Output = Seq[DoubleLayer]

def step(x: Input, children: Stream[Output]): Output = ???

def treeNet(x: Tree[Input]): Tree[Output] = {
  x.scanr(step)
}
```

---

# NEURO NETWORK IS FUNCTIONAL PROGRAMMING

---

• Deep Learning Name	• Functional Name
• Learned Vector	• Constant in metaprogramming
• Encoding RNN	• Fold
• Generating RNN	• Unfold
• General RNN	• Accumulating Map
• Bidirectional RNN	• Zipped Left/Right Accumulating Maps
• Conv Layer	• “Window Map”
• TreeNet	• Catamorphism

---

# WHAT

---

**BIOLOGICAL?**

**YES**

**FEATURE ENGINEERING?**

**YES**

**FUNCTIONAL PROGRAMMING?**

**YES**

**METAPROGRAMMING?**

**YES**



# MONADIC DEEP LEARNING

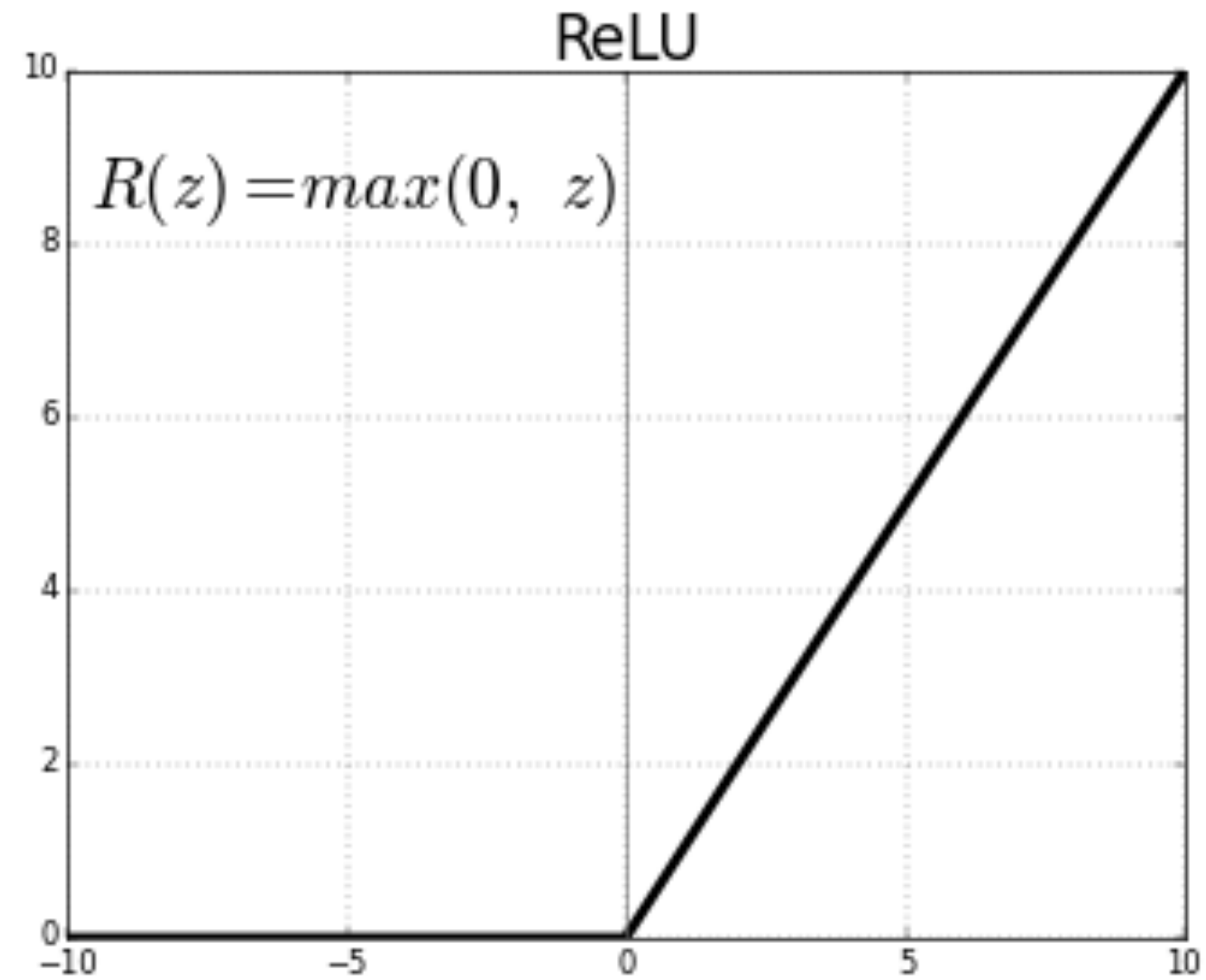
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*we have done ...*

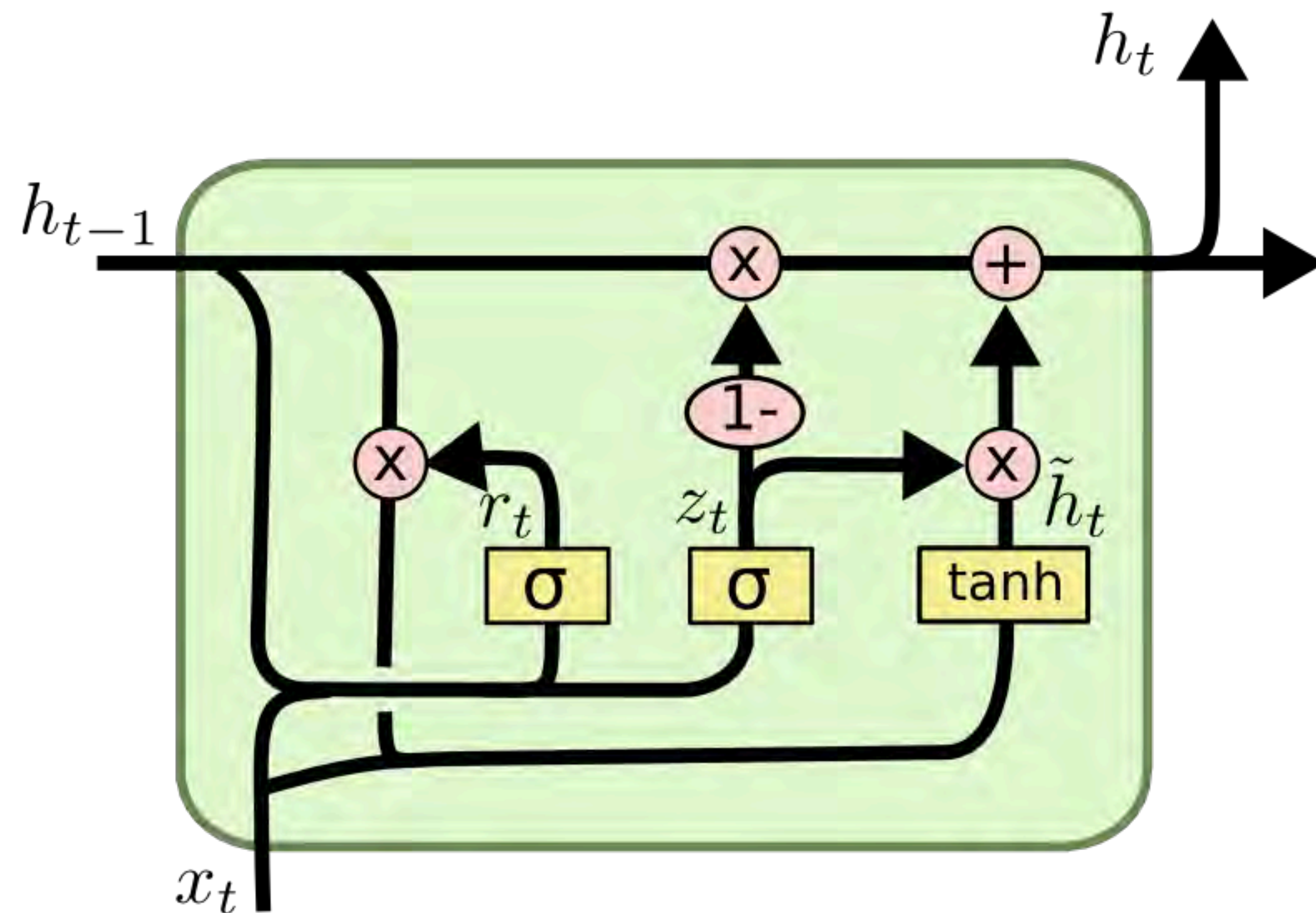
---

# IF ... ELSE ...

---



# IF ... ELSE ...



$$z_t = \sigma (W_z \cdot [h_{t-1}, x_t])$$

$$r_t = \sigma (W_r \cdot [h_{t-1}, x_t])$$

$$\tilde{h}_t = \tanh (W \cdot [r_t * h_{t-1}, x_t])$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$



# MIXTURE OF EXPERTS

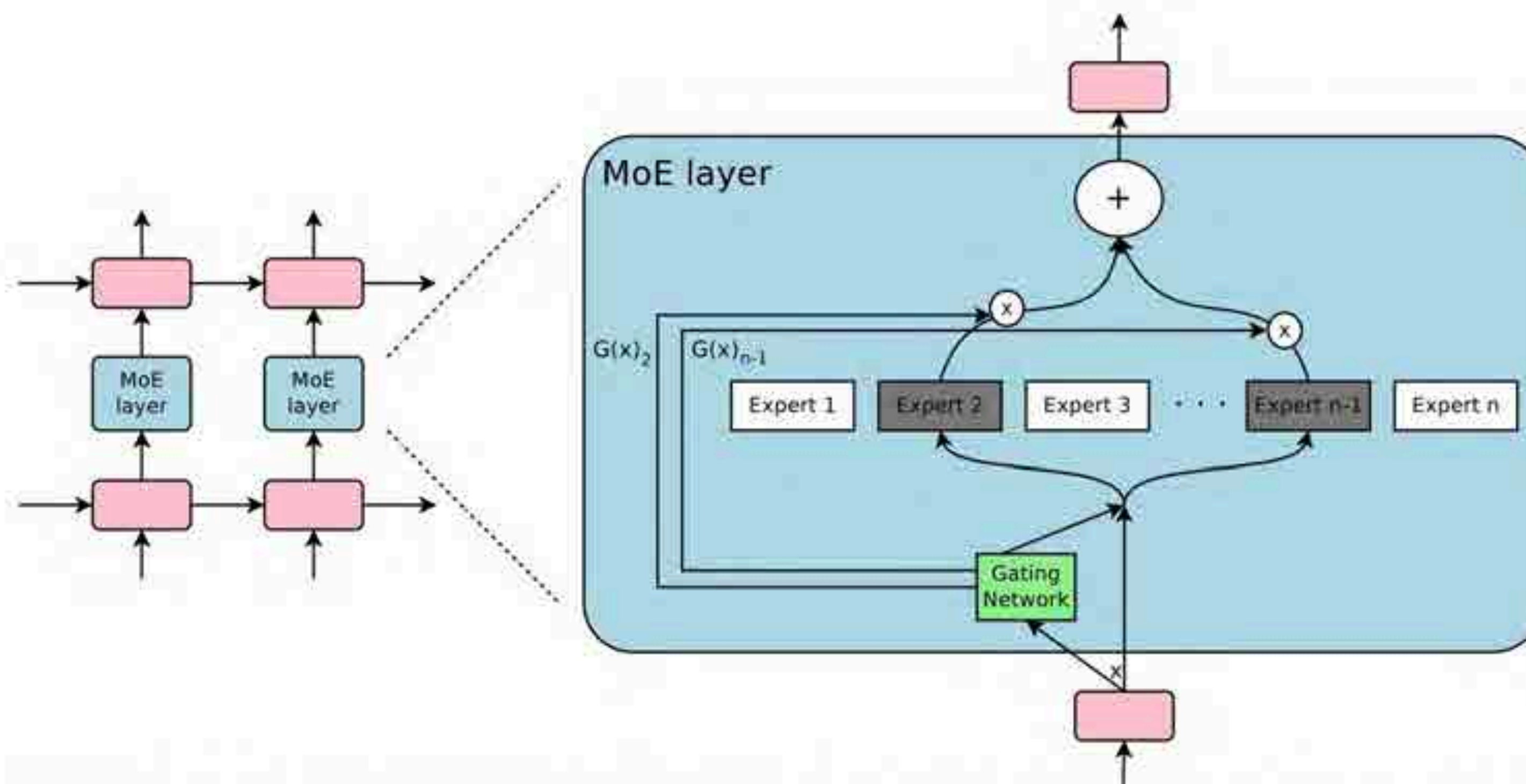


Figure 1: A Mixture of Experts (MoE) layer embedded within a recurrent language model. In this case, the sparse gating function selects two experts to perform computations. Their outputs are modulated by the outputs of the gating network.

---

# NAIVE GATED NET

---

```
type Input = INDArraryLayer
type Output = INDArraryLayer
type Condition = (DoubleLayer, DoubleLayer)

def leftSubnet(input: Input): Output = ???
def rightSubnet(input: Input): Output = ???
def gate(input: Input): Condition = ???

def naiveGatedNet(input: Input): Output = {
  val condition = gate(input)
  if (condition._1.predict.blockingAwait > condition._2.predict.blockingAwait) {
    conditionLeft * leftSubnet(input)
  } else {
    conditionRight * rightSubnet(input)
  }
}
```

---

# NAIVE GATED NET

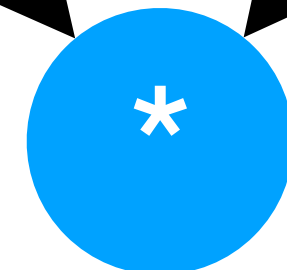
---

gate.\_1

gate.\_2

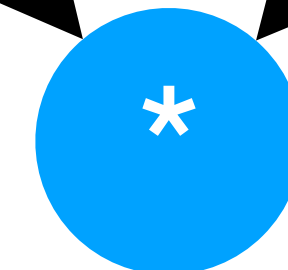
gate.\_1

leftSubnet



gate.\_2

rightSubnet





---

# MONADIC GATED NET

---

```
def monadicGatedNet(input: Input): Output = {  
  val condition = gate(input)  
  val gatedForward =  
    (condition._1.forward.tuple2(condition._2.forward)).flatMap { pair =>  
      if (pair._1.data > pair._2.data) {  
        (condition._1 * leftSubnet(input)).forward  
      } else {  
        (condition._2 * rightSubnet(input)).forward  
      }  
    }  
  INDArrayLayer(gatedForward)  
}
```

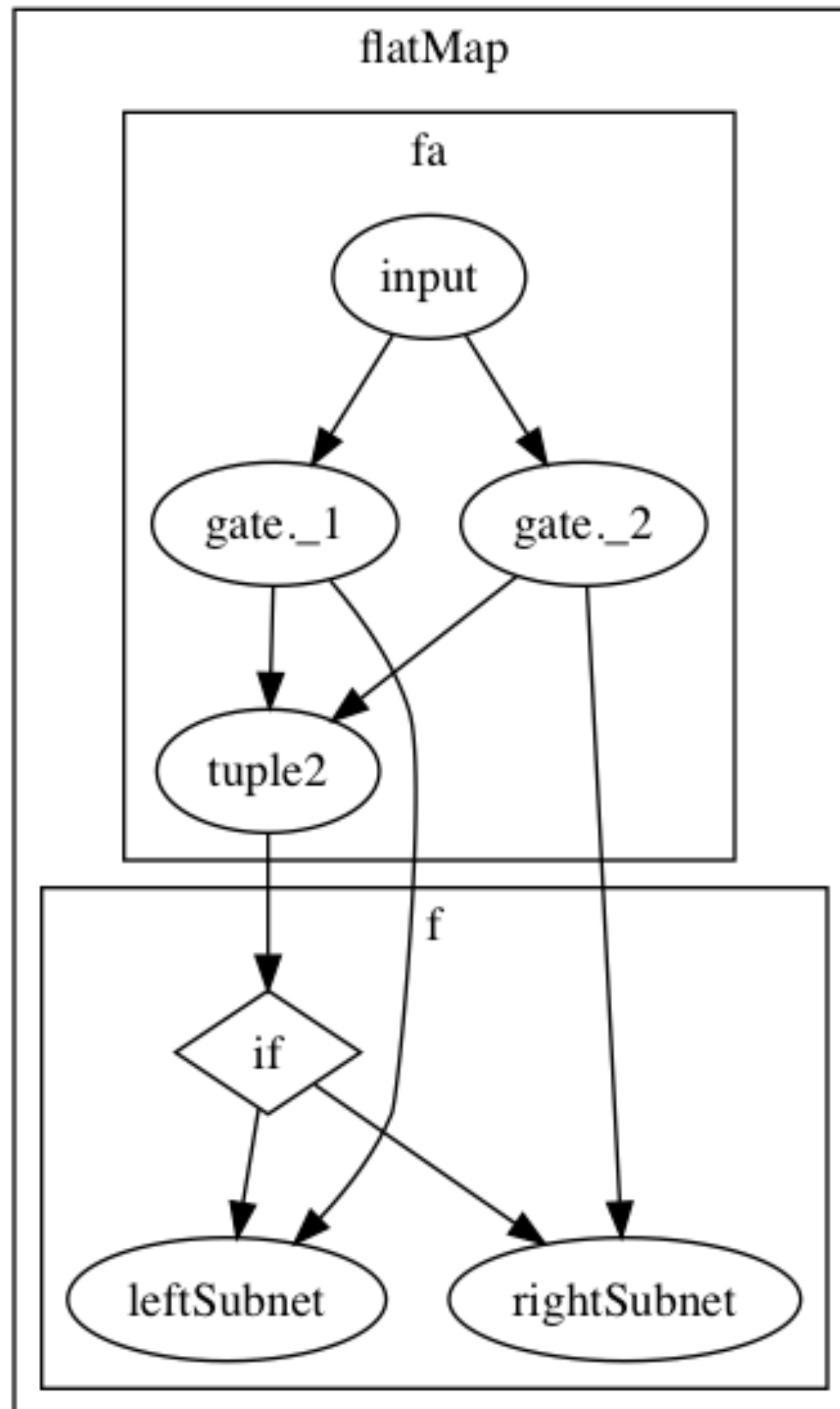
---

# MONADIC GATED NET

---

```
package scalaz
trait Monad[F[_]] extends Apply[F[_]] {
  def point(a: => A): F[A]
  def bind[A, B](fa: F[A])(f: A => F[B]): F[B]
}
```

# MONADIC GATED NET



```
def monadicGatedNet(input: Input): Output = {  
  val condition = gate(input)  
  val gatedForward =  
    (condition._1.forward.tuple2(condition._2.forward))  
    .flatMap { pair =>  
      if (pair._1.data > pair._2.data) {  
        (condition._1 * leftSubnet(input)).forward  
      } else {  
        (condition._2 * rightSubnet(input)).forward  
      }  
    }  
  INDArrayLayer(gatedForward)  
}
```



---

# PARALLEL GATED NET

---

```
def parallelGatedNet(input: Input): Output = {  
  val condition: (DoubleLayer, DoubleLayer) = gate(input)  
  val parallelCondition1Forward = Parallel(condition._1.forward)  
  val parallelCondition2Forward = Parallel(condition._2.forward)  
  val Parallel(tupled) = condition1ForwardParallel.tuple2(condition2ForwardParallel)  
  val gatedForward = tupled.flatMap { pair =>  
    if (pair._1.data > pair._2.data) {  
      (condition._1 * leftSubnet(input)).forward  
    } else {  
      (condition._2 * rightSubnet(input)).forward  
    }  
  }  
  INDArrayLayer(gatedForward)  
}
```

---

# THOUGHTWORKS EACH

---

```
def eachGatedNet(input: Input): Output = INDArrayLayer(monadic[Do] {  
  val condition: (DoubleLayer, DoubleLayer) = gate(input)  
  val parallelCondition1Forward = Parallel(condition._1.forward)  
  val parallelCondition2Forward = Parallel(condition._2.forward)  
  val Parallel(tupled) = condition1ForwardParallel.tuple2(condition2ForwardParallel)  
  val pair: (Tape[Double, Double], Tape[Double, Double]) = tupled.each  
  if (pair._1.data > pair._2.data) {  
    (condition._1 * leftSubnet(input)).forward.each  
  } else {  
    (condition._2 * rightSubnet(input)).forward.each  
  }  
})
```

# EXPRESSION PROBLEM

---

*we have done ...*



# THE EXPRESSION PROBLEM

type \ op	Evaluate	Stringify	New op
Constant	✓	✓	✓
BinaryPlus	✓	✓	✓
New type	☹	☹	

Attila Magyar, 2016  
Microsec Ltd.

---

# HYPERPARAMETER IN DEEPLARNING.SCALA

---

```
val hyperparameters1 = Factory[Builtins with FixLearningRate].newInstance(
  learningRate = 0.001
)
val weight1 = hyperparameters1.INDArrayWeight(Nd4j.randn(10, 10))
val layer1[Input](input: Input): hyperparameters1.INDArrayLayer = {
  tanh(input dot weight1)
}
```

```
val hyperparameters2 = Factory[Builtins with FixLearningRate].newInstance(
  learningRate = 0.002
)
val weight2 = hyperparameters2.INDArrayWeight(Nd4j.randn(10, 10))
val layer2[Input](input: Input): hyperparameters2.INDArrayLayer = {
  tanh(input dot weight2)
}
```

```
val hyperparameters3 = Factory[Builtins].newInstance()
def twoLayerNeuralNetwork(input: INDArray): hyperparameters3.INDArrayLayer = {
  val layer1Output: hyperparameters1.INDArrayLayer = layer1(input)
  layer2(layer1Output)
}
```

---

# PLUGIN

---

```
val hyperparameters = Factory[
  Plugin1 with Plugin2 with Plugin3
].newInstance(
  hyperparameterKey1 = hyperparameterValue1,
  hyperparameterKey2 = hyperparameterValue2,
  hyperparameterKey3 = hyperparameterValue3
)
```



---

# CREATING PLUGIN

---

```
trait Softmax extends Builtins {  
  def softmax[Scores: DeepLearning.Aux[?, INDArrary, INDArrary]]  
    (scores: Scores): INDArraryLayer = {  
    val expScores = hyperparameters.exp(scores)  
    expScores / expScores.sum(1)  
  }  
}
```

```
val hyperparameters = Factory[Softmax].newInstance()  
val probabilities = hyperparameters.softmax(Nd4j.randn(10, 10))
```

---

# CREATING PLUGIN

---

```
trait FixedLearningRate extends Builtins {  
  def learningRate: Double  
  trait INDArrayOptimizerApi extends super.INDArrayOptimizerApi {  
    private lazy val delta0: INDArray = super.delta * learningRate  
    override def delta: INDArray = delta0  
  }  
  override type INDArrayOptimizer <: Optimizer with INDArrayOptimizerApi  
}
```

```
Factory[Builtins with FixLearningRate].newInstance(learningRate = 0.001)
```



# **AUTOMATIC HYPERPARAMETER TUNING**





ThoughtWorks®

# FUTURE WORK

---

*we have done ...*

---

# FUTURE WORK

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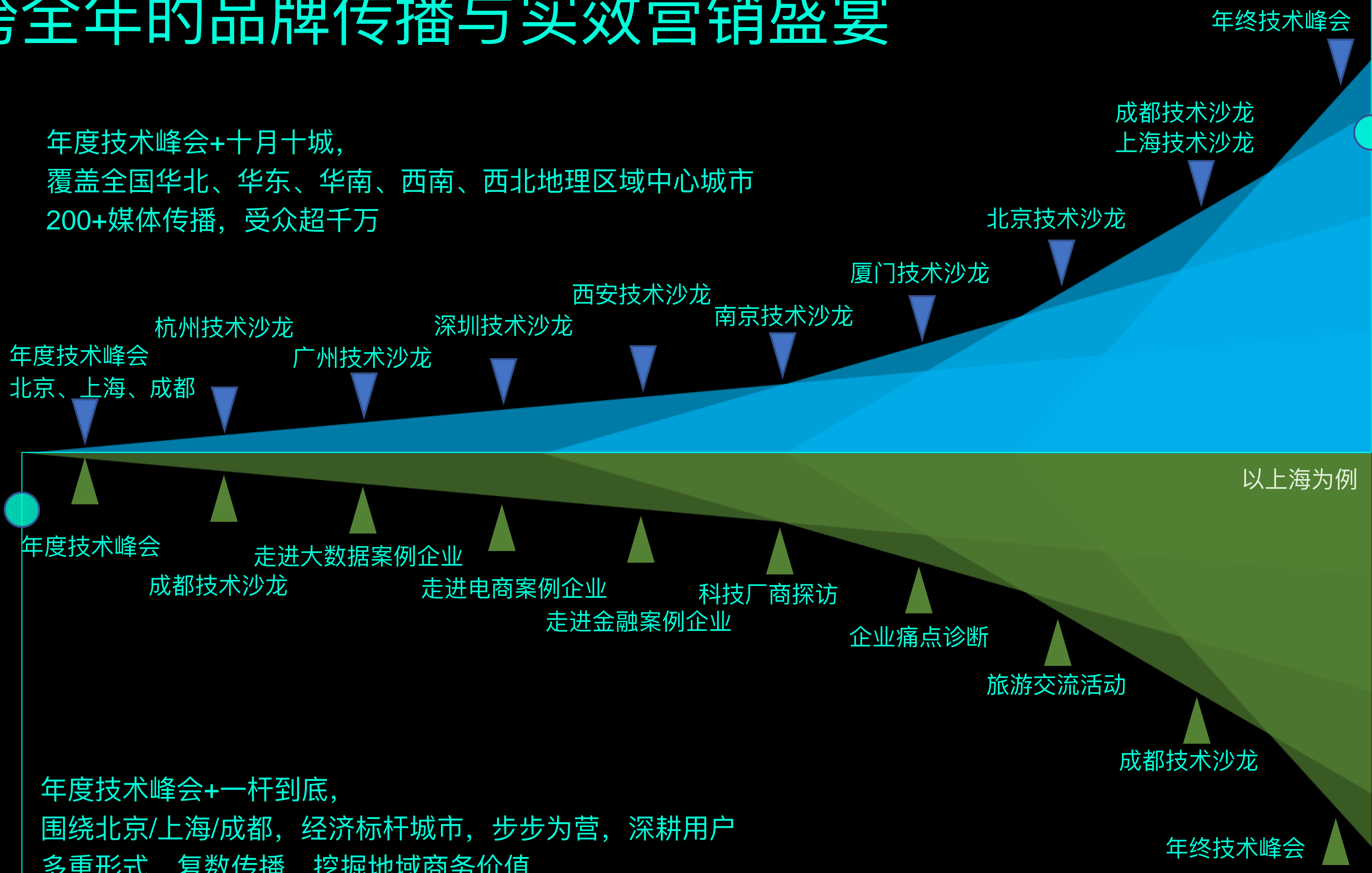
**1. NEW BACKEND**

**2. DISTRIBUTED MODEL**

# 横跨全年的品牌传播与实效营销盛宴

年度技术峰会+十月十城，  
覆盖全国华北、华东、华南、西南、西北地理区域中心城市  
200+媒体传播，受众超千万

全域连横



同城合纵

年度技术峰会+一杆到底，  
围绕北京/上海/成都，经济标杆城市，步步为营，深耕用户  
多重形式，复数传播，挖掘地域商务价值

合纵连横，在中国开发者群体中缔造品牌营销奇迹





# 中生代技术

FRESHMAN TECHNOLOGY



ArchData技术峰会全国巡回

上海9月，北京9月，成都10月，南京10月，  
长沙11月，广州11月

中生代咨询内训

技术架构，研发管理，敏捷开发，大数据  
微服务，AI，机器学习

中生代人才内推

对接研发主管，内推精准人才