

“Deep learning from scratch”

~ Chapter 5 “*Back propagation*” ~

Chapter 5.1 Computational graph

Chapter 5.2 Chain rule

Chapter 5.3 backward propagation

2018/06/18

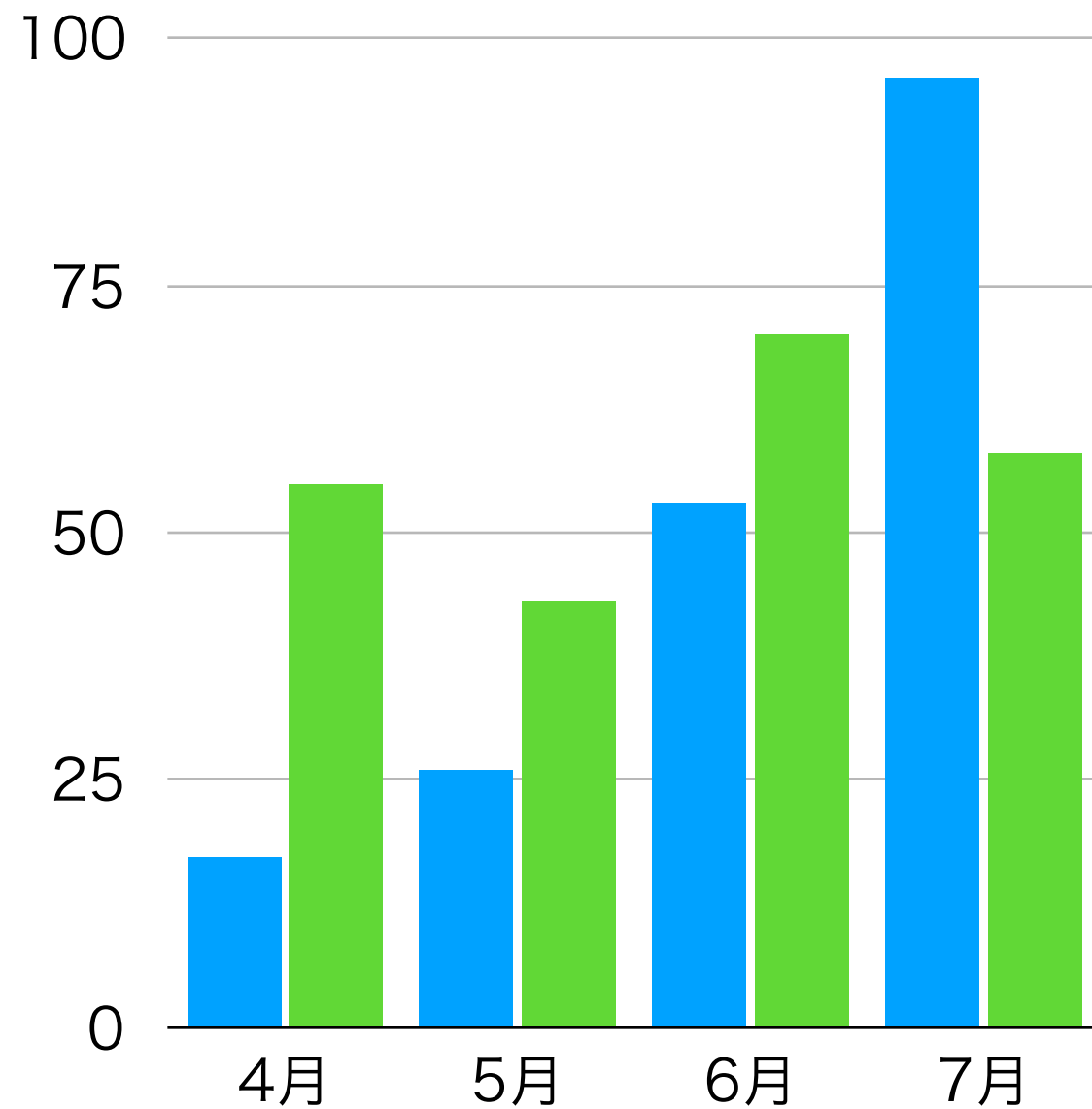
Yousuke Ogata

5.1 Computational Graph

- To understand backpropagation, explain by...
 - Mathematics
 - > Strict, but toooooooo hard to learn ***all***
 - Computational graph
 - > could be understood visually: more easier...?

ref) lecture in Stanford univ, “CS231n”
(<http://cs231n.github.io/>)

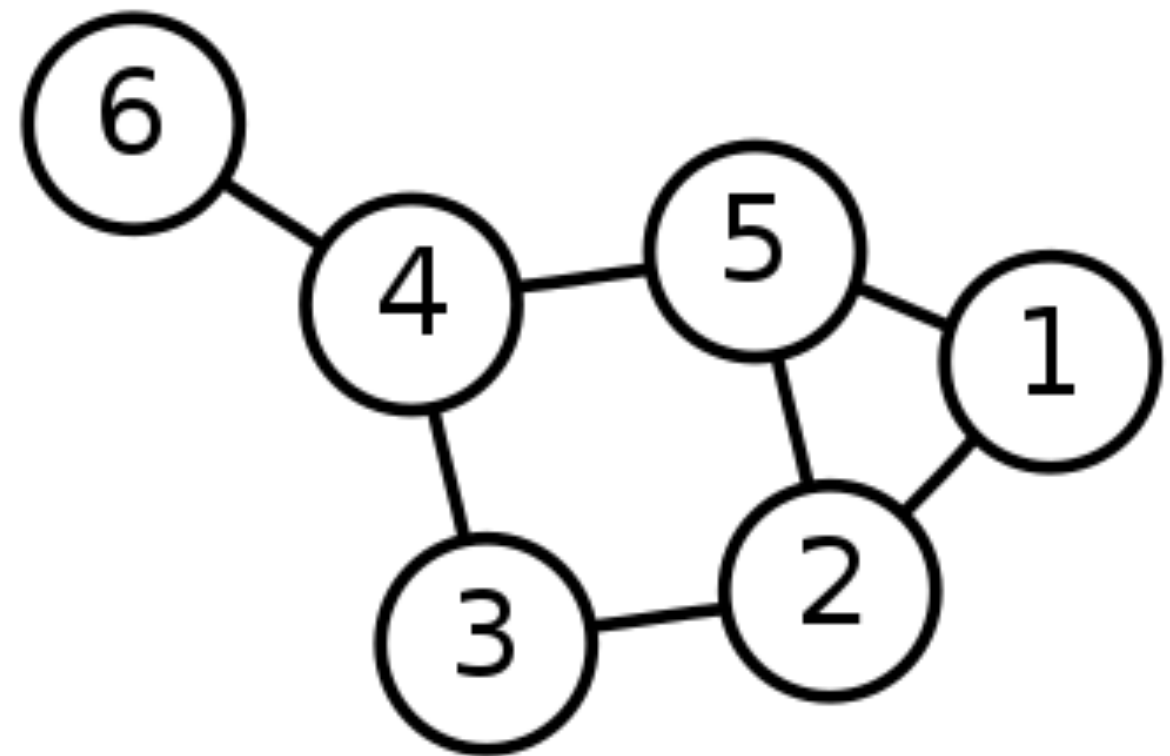
What is the “Graph?”



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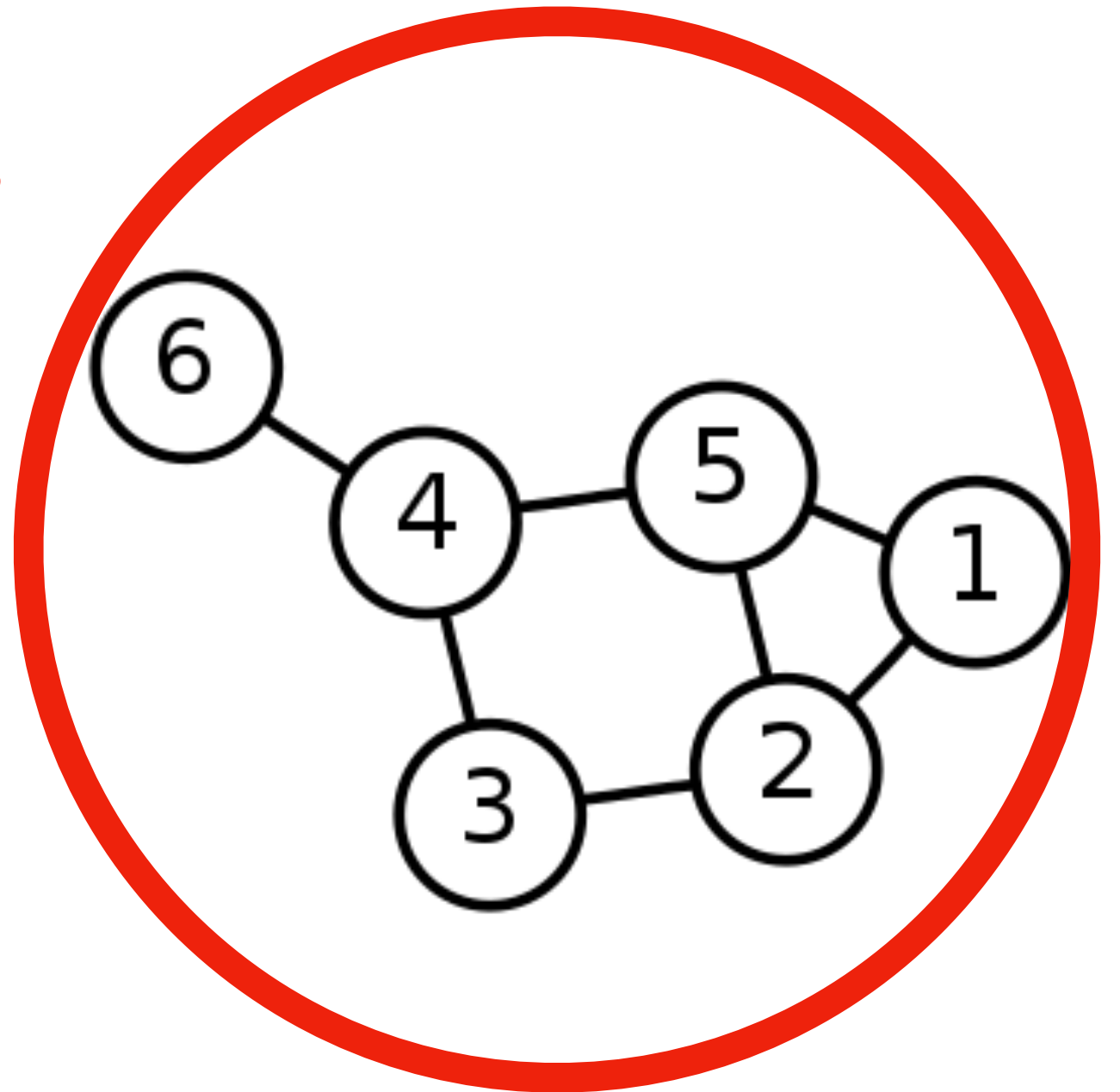


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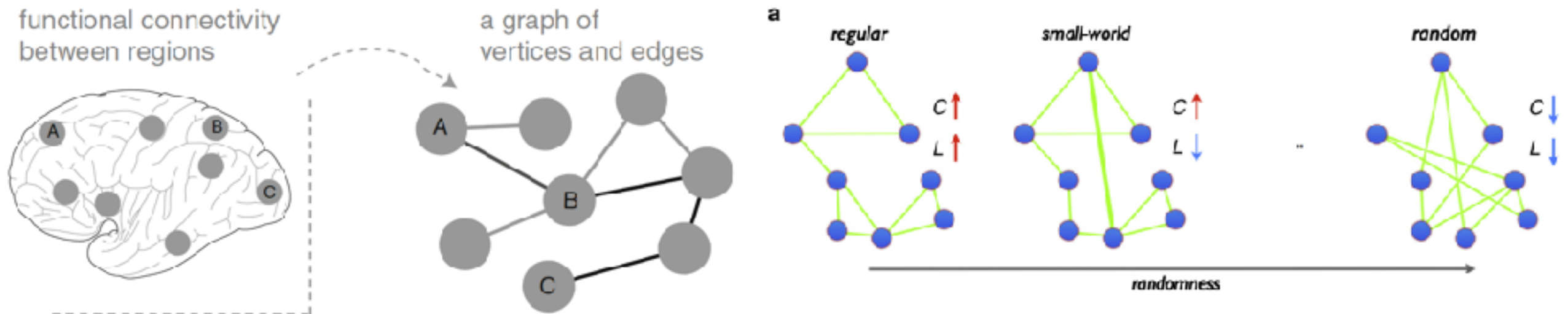
(Wikipedia: “Graph theory”
https://en.wikipedia.org/wiki/Graph_theory , 2018/06/15)

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Graph theory (in Neuroimaging)



- Construct from **Vertices (Nodes)** and **Edges**
 - Vertex : ROI or single-voxel
 - Edge : functional connectivity
 - Path : a sequence of vertices in which all succeeding vertices are connected by edges
- To analyze relationship of graph, calculate
 - Distance : the minimum length among all paths connecting vertices
 - Degree : the number of edges connecting to it

Cf) Seven Bridges of Königsberg, four-color problem etc...

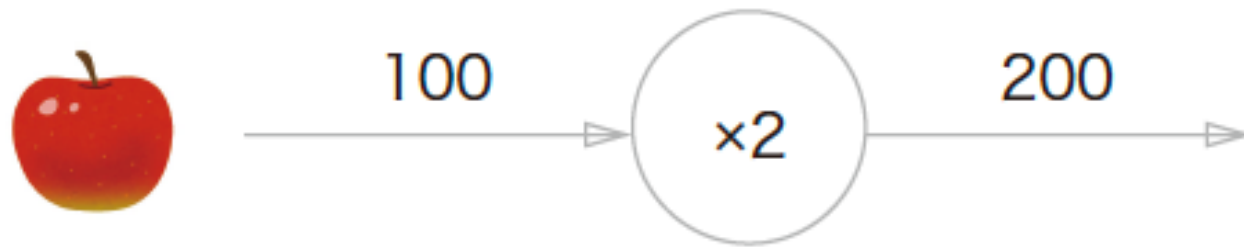
Solving problems with computational graph

- Q1: Taro bought two apples. Apple is priced ¥100 (with exclude VAT:10%).
How much taro needs to pay?



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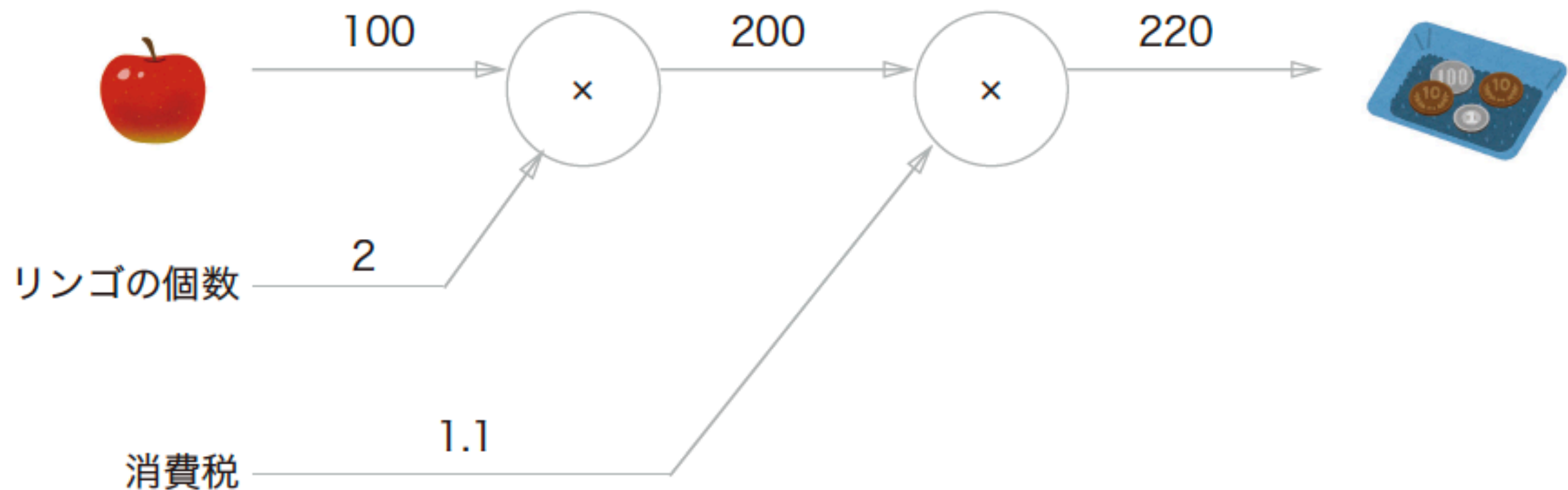
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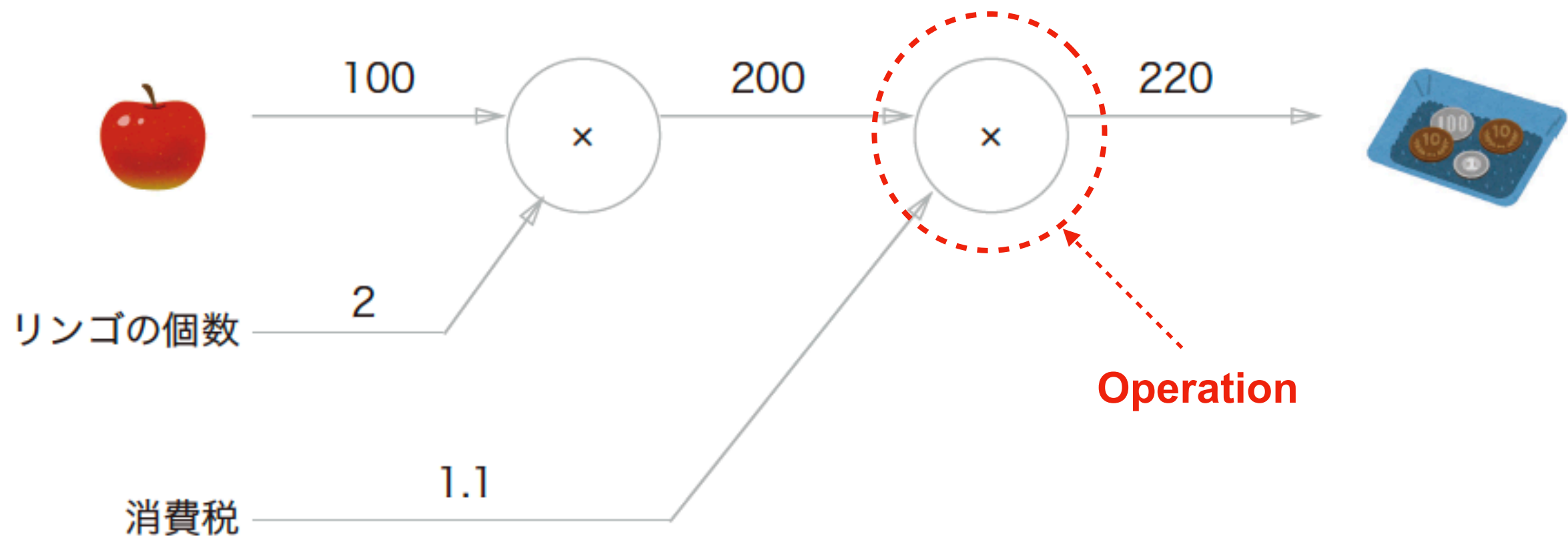
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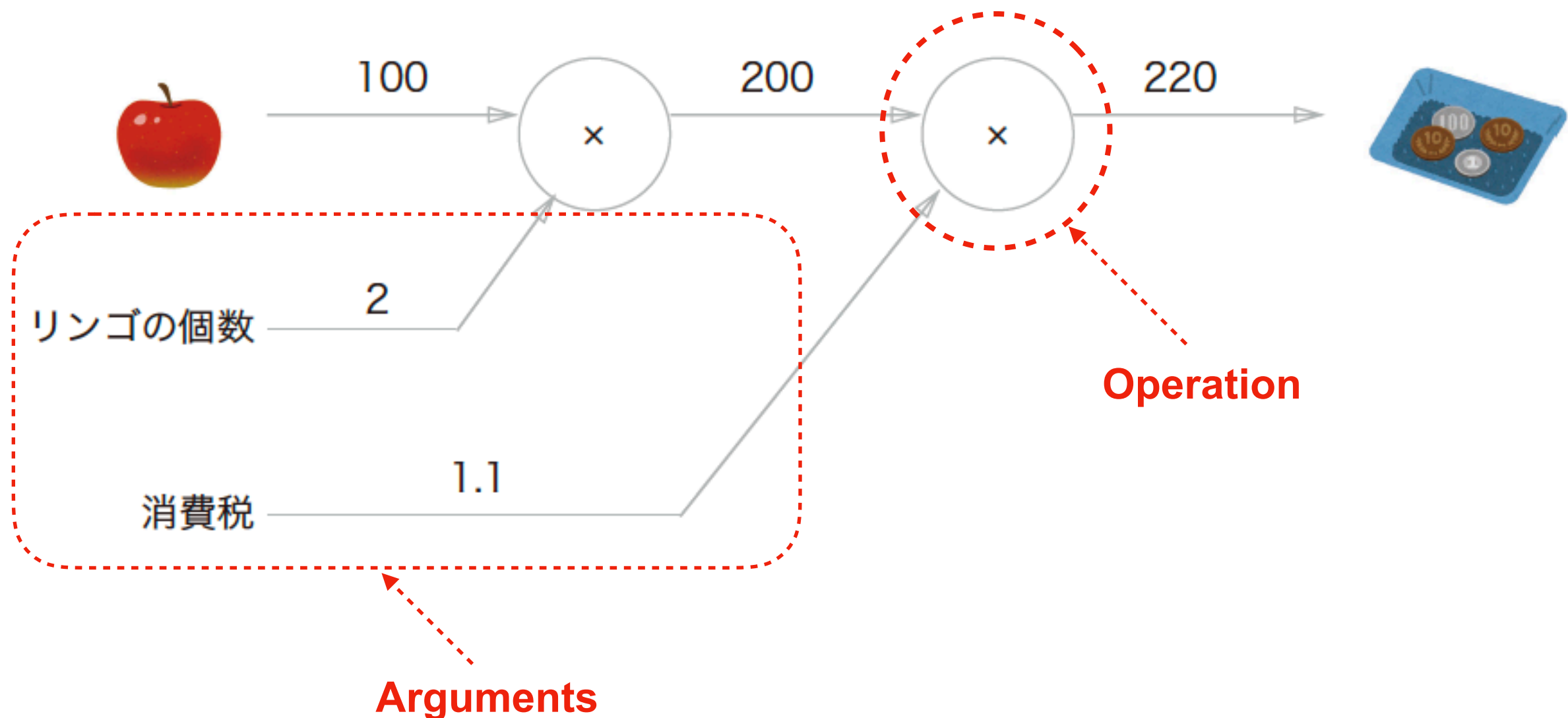
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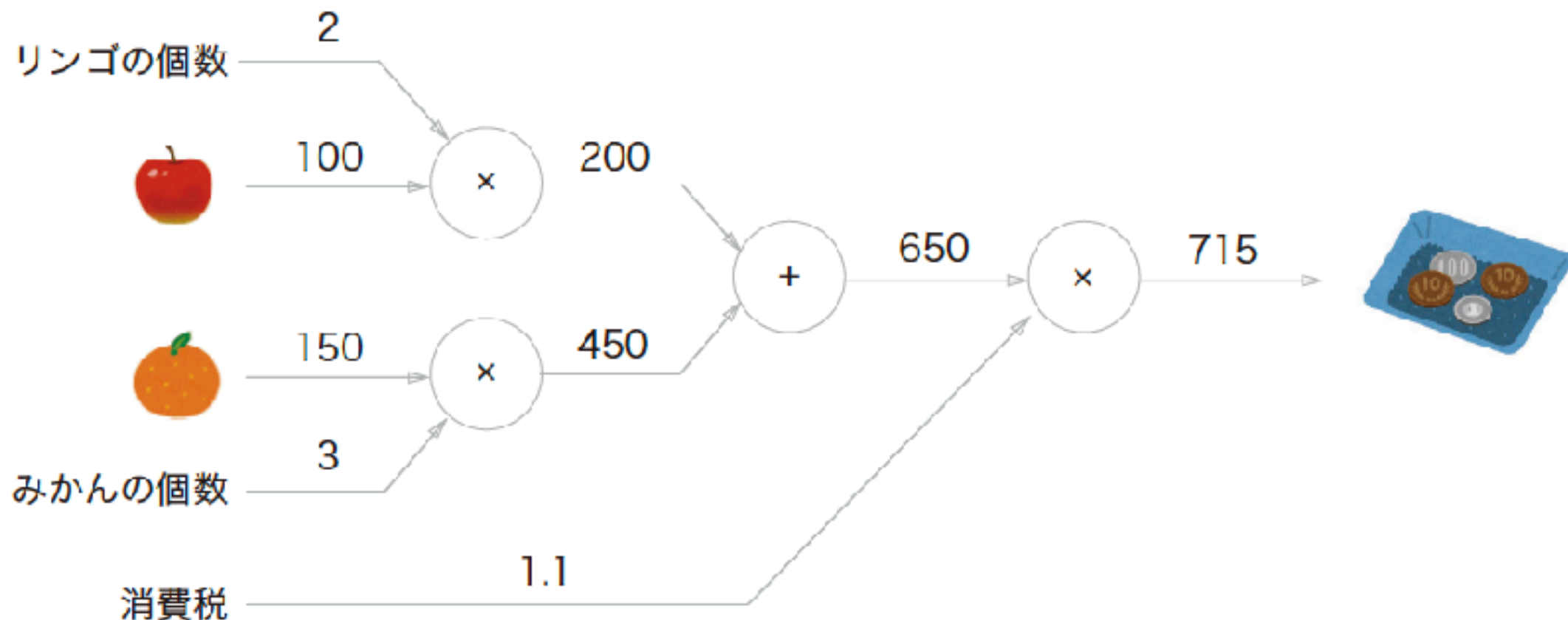


Solving problems with computational graph (2)

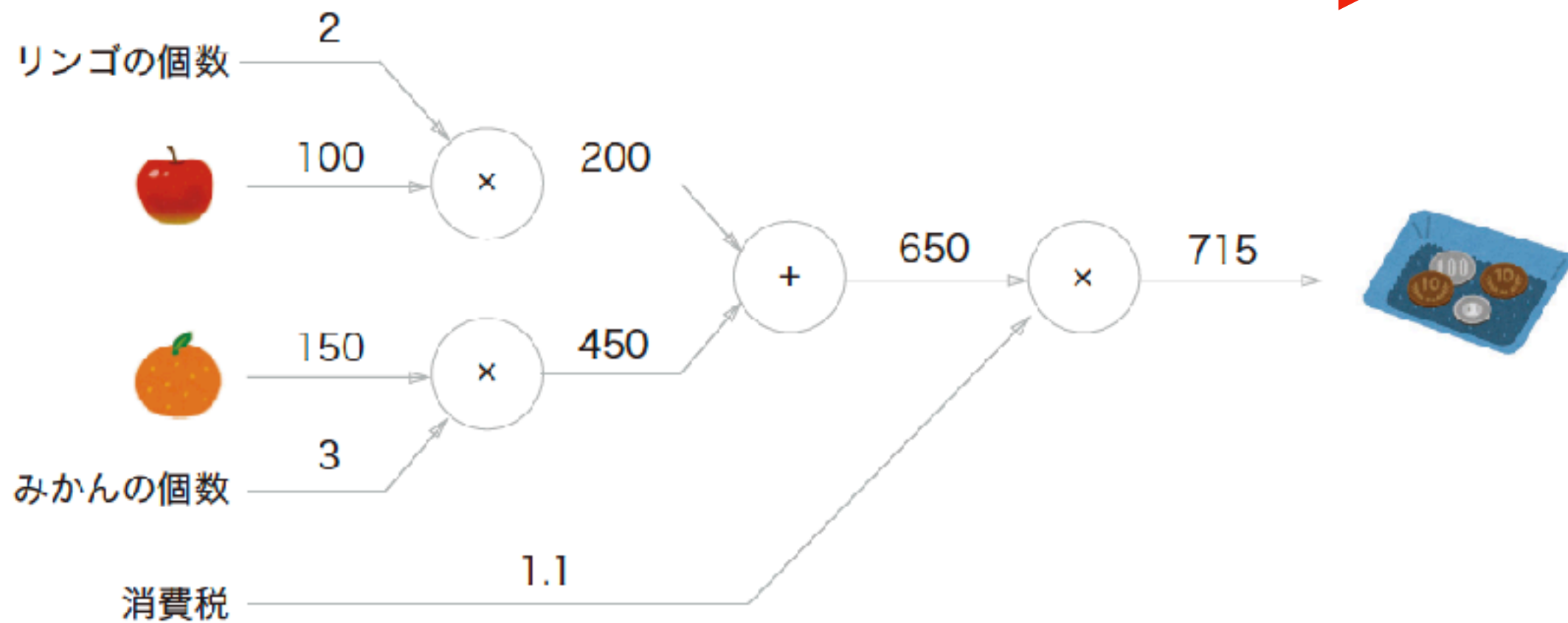
- Q2: Taro bought two apples and three oranges.
Apple is priced ¥100, Orange is priced ¥150(VAT:10%).
How much taro needs to pay?

Solving problems with computational graph (2)

- Q2: Taro bought two apples and three oranges. Apple is priced ¥100, Orange is priced ¥150(VAT:10%). How much taro needs to pay?



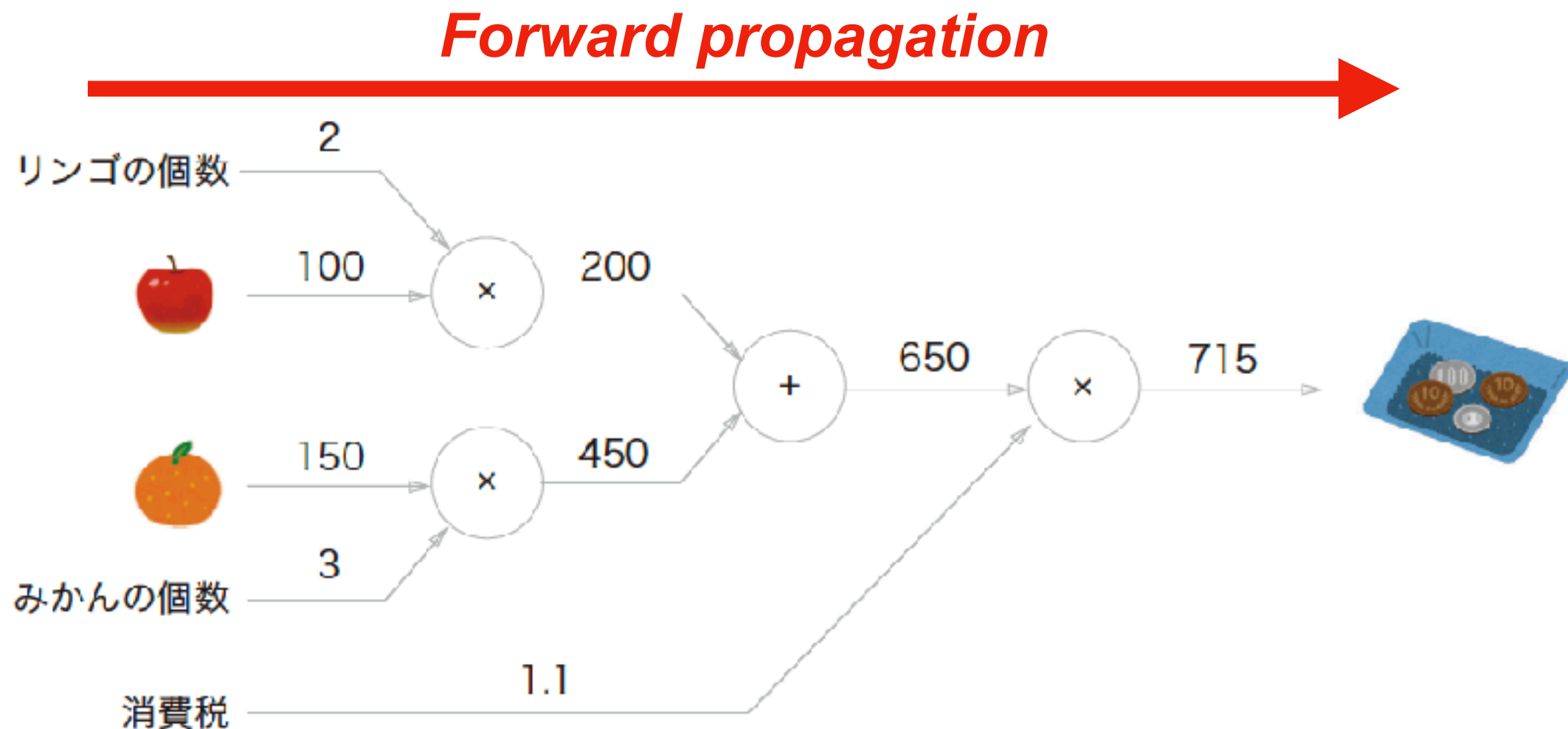
Forward propagation



Backward propagation

computes values from inputs(left) to output(right)

=> **forward propagation**



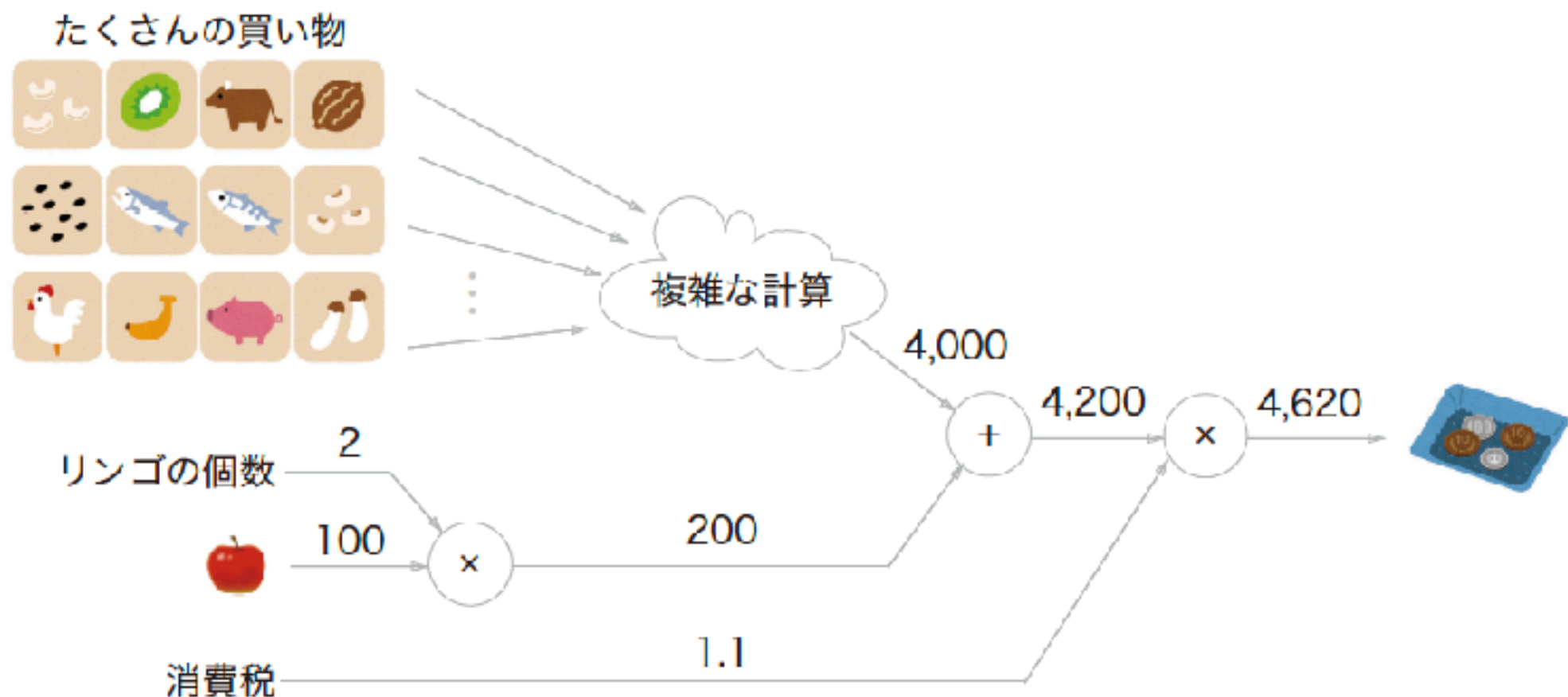
Backward propagation

transfer gradient from output(right) to inputs(left)

=> **Backward propagation**

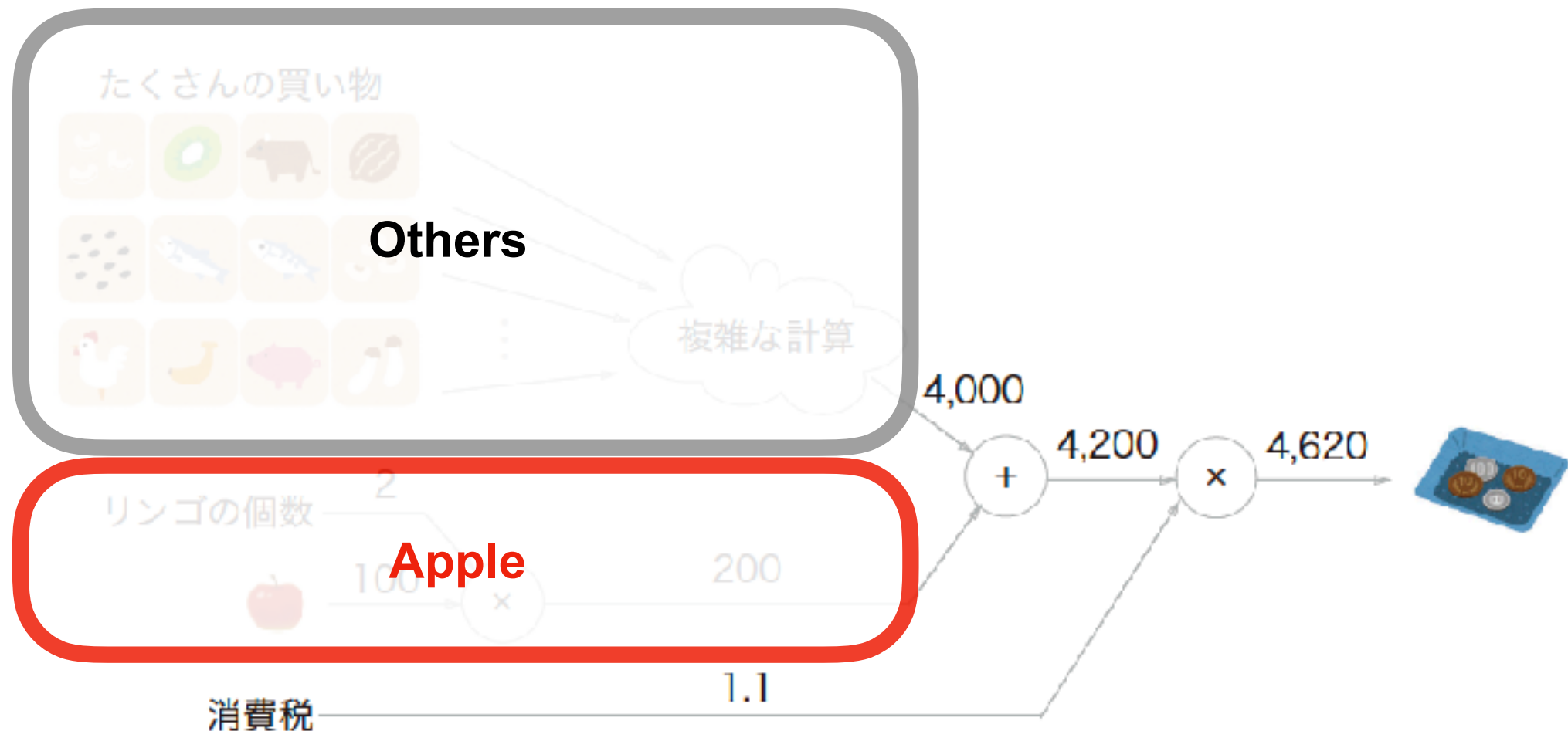
“Local” processing

- Computational graph allowed us to obtain a result by transferring “local operations”
=> can ignore “global” processing



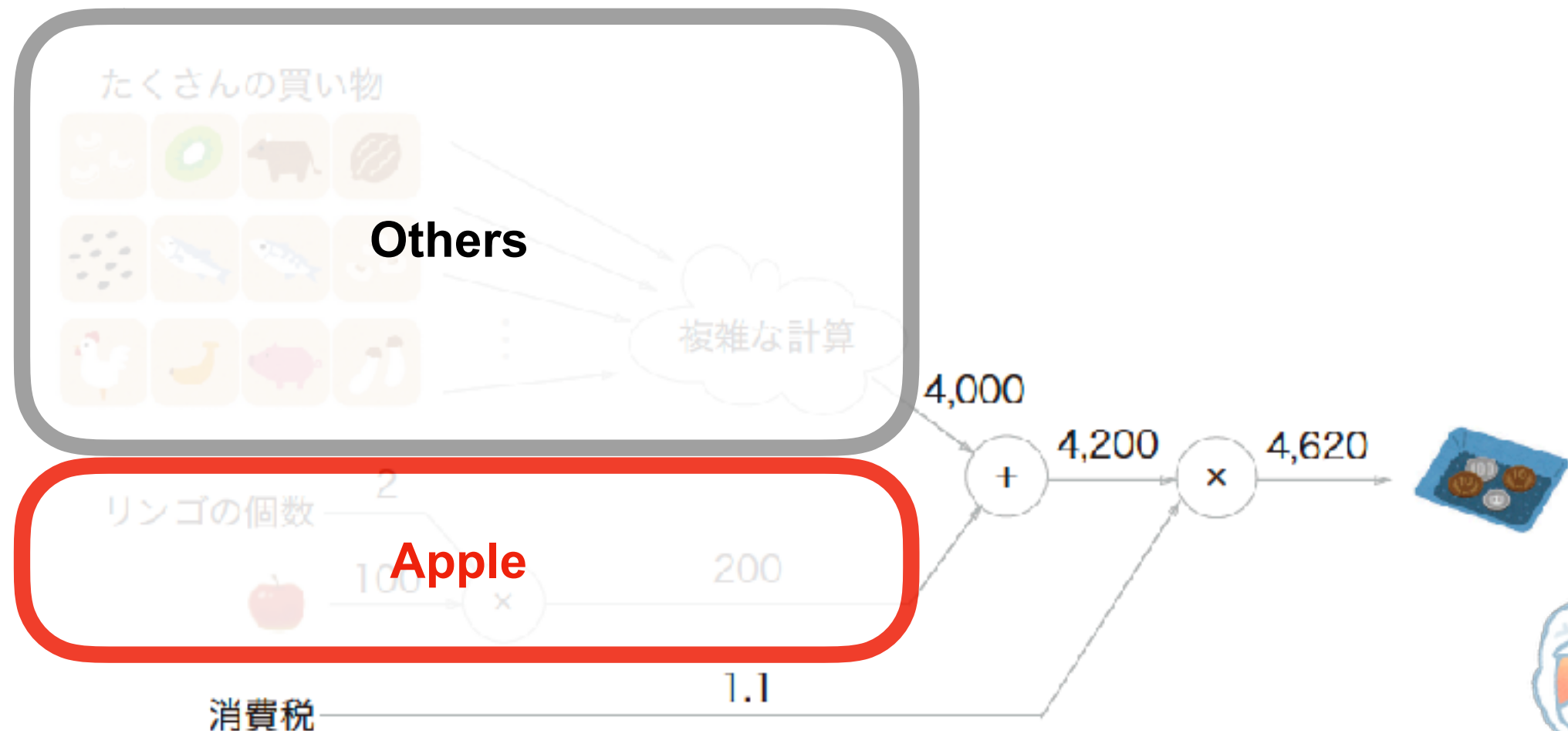
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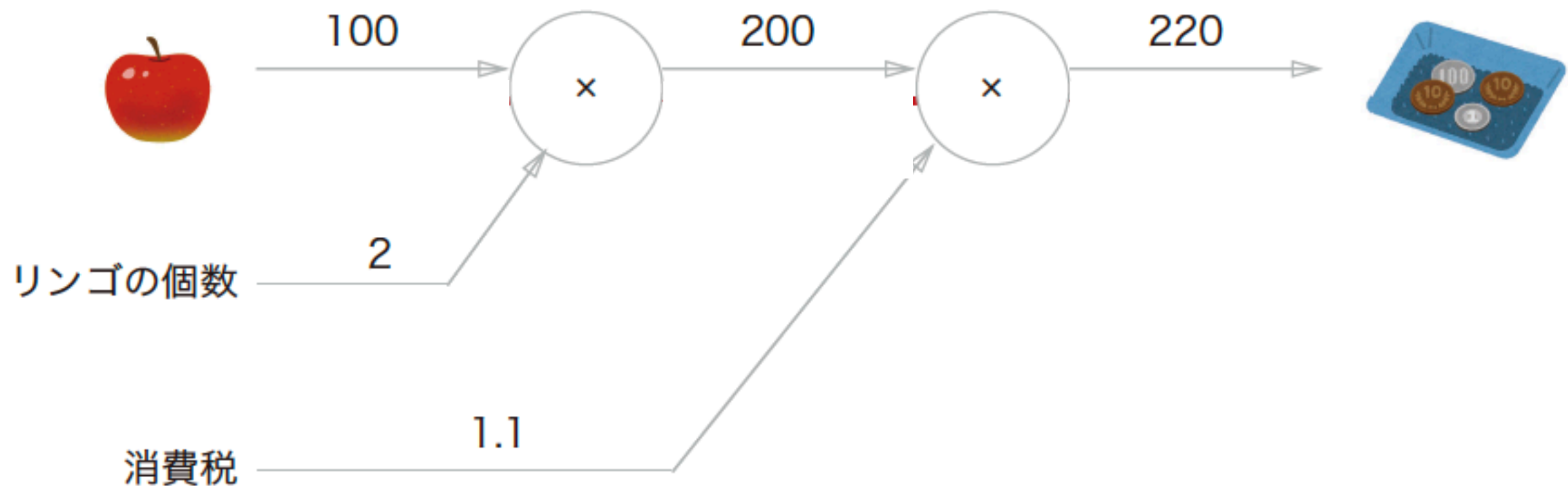
Just means...

= can focus only “local” operations in each nodes



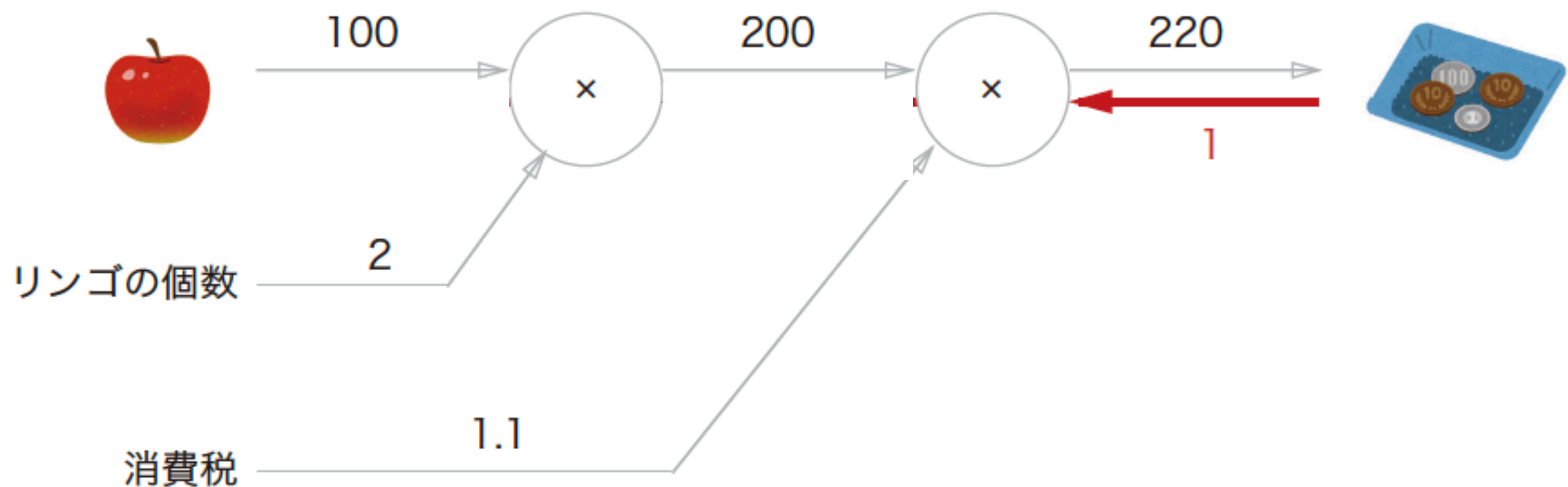
Backward propagation

- Why computational graph was used for explain backward propagation??
=> calculate gradient efficiently



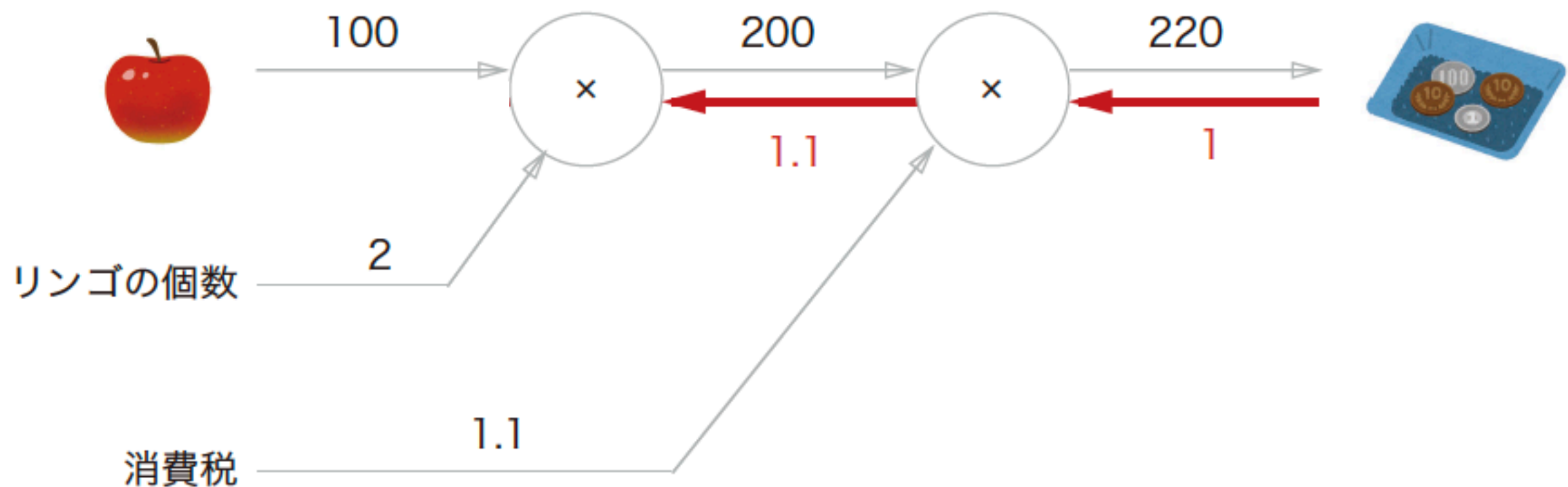
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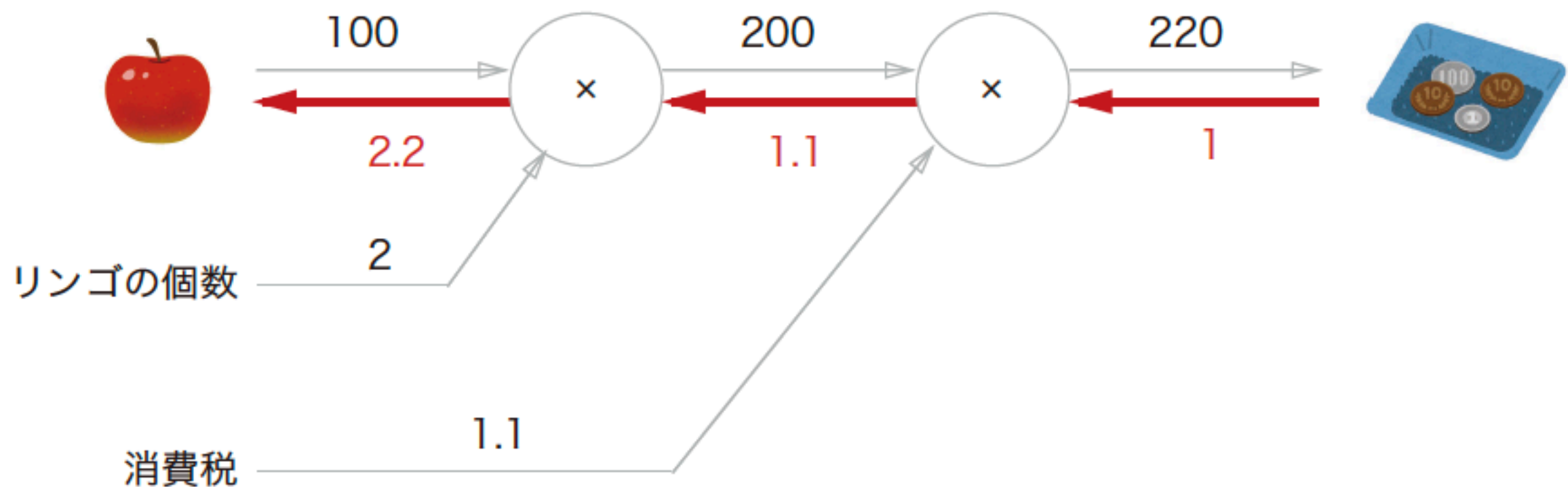
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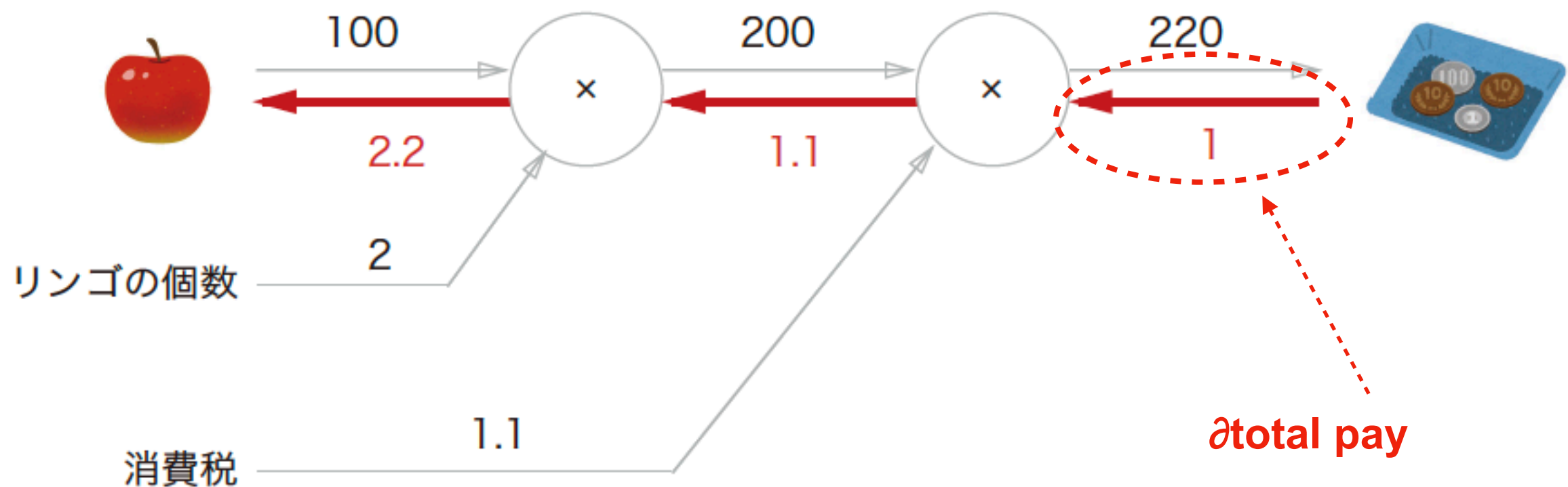
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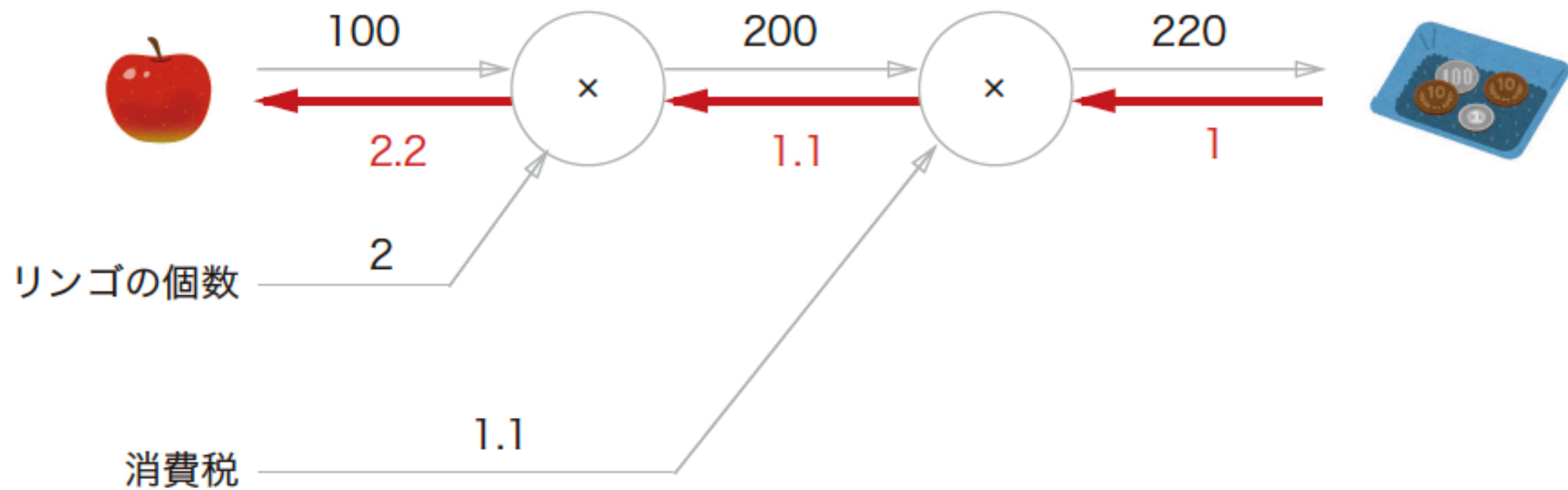


Backward propagation

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Forward propagation: price(or pay)



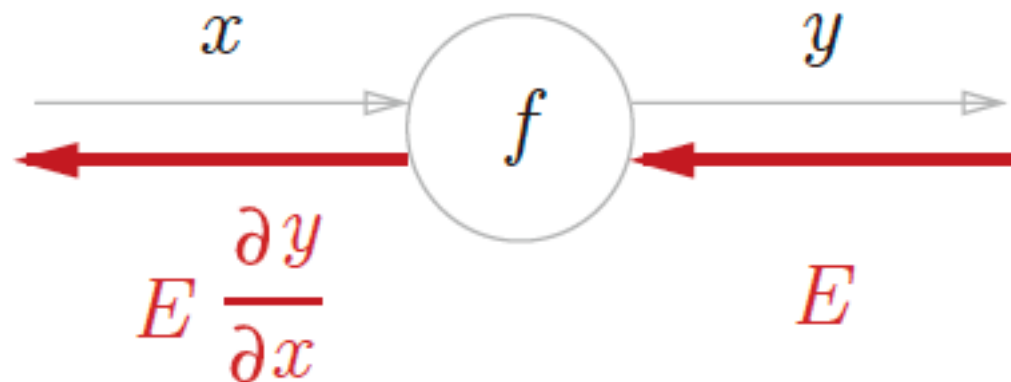
Backward propagation: fluctuation of price

5.2 Chain rule

- Chain rule: a formula for computing the derivative of the composition of two or more functions.
(from wikipedia, “Chain rule”)

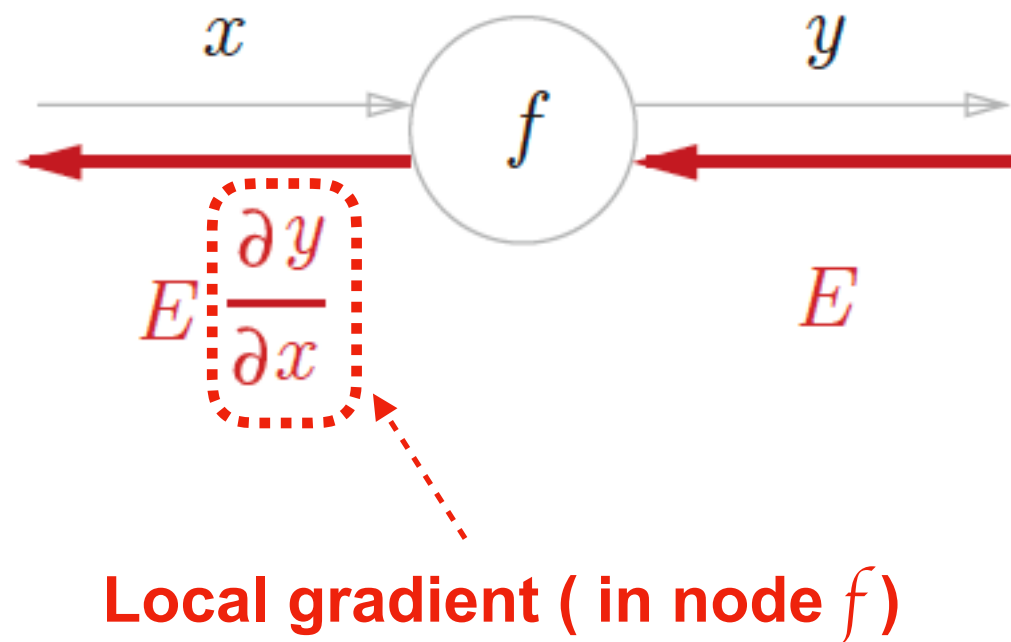
5.2 Chain rule

- In backpropagation, it pass “local” gradient to previous node.
=> based on chain rule



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Composite function

- Composite function: function composed of multiple functions

$$z = (x + y)^2$$



$$z = t^2$$

$$t = x + y$$

Chain rule:

When a function is represented by a composite function, the derivative of the composite function can be represented by the product of the differentiation of the each functions.

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$$\begin{array}{l} z = t^2 \\ t = x + y \end{array} \quad \rightarrow \quad \frac{\partial z}{\partial x} = \frac{\partial z}{\partial t} \frac{\partial t}{\partial x}$$

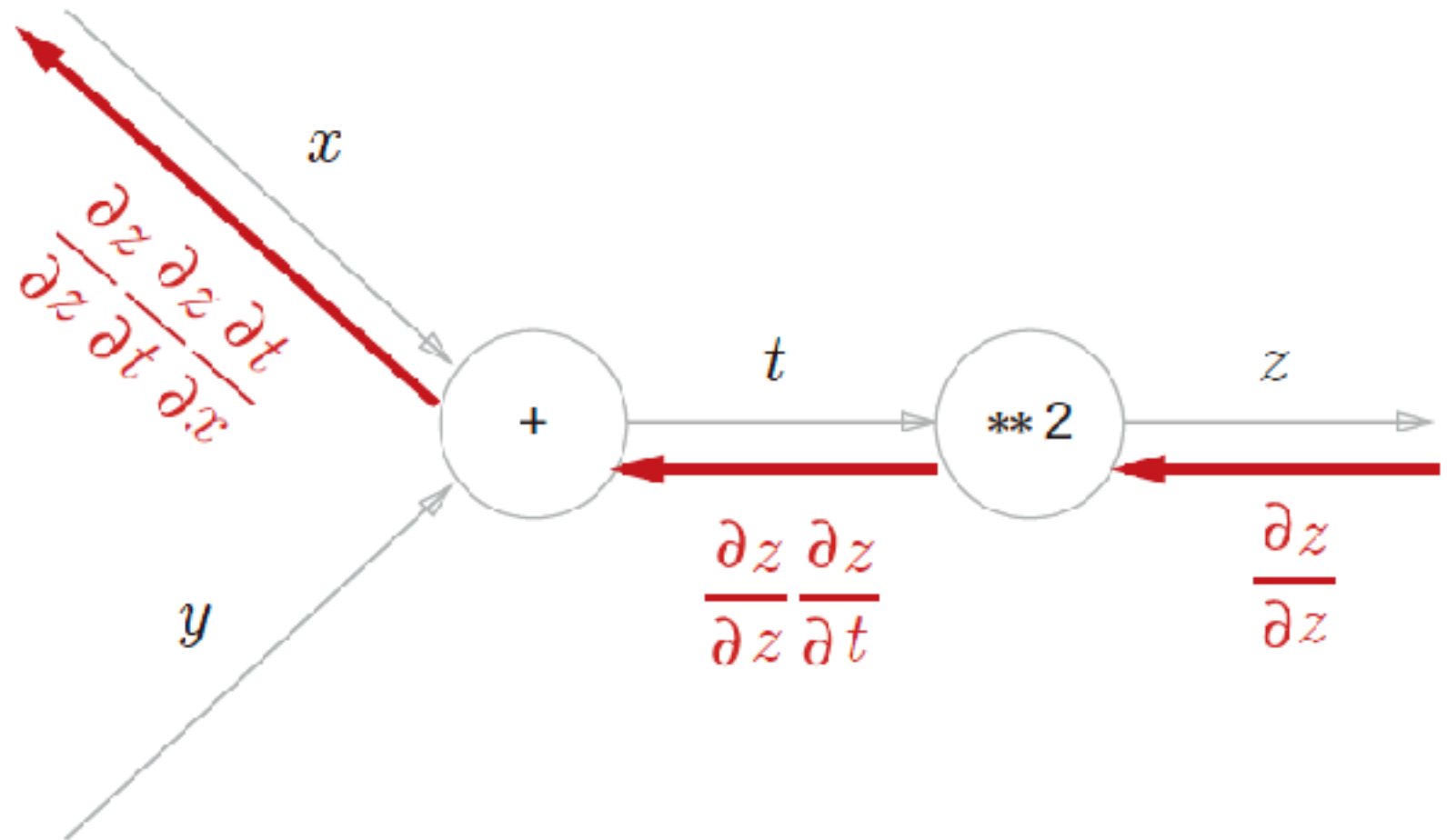
Example:

$$\begin{array}{l} \frac{\partial z}{\partial t} = 2t \\ \frac{\partial t}{\partial x} = 1 \end{array} \quad \frac{\partial z}{\partial x} = \frac{\partial z}{\partial t} \frac{\partial t}{\partial x} = 2t \cdot 1 = 2(x + y)$$

Chain rule in graph

$$z = t^2$$

$$t = x + y$$



- In the backpropagation, the product of the input to the node and local derivative(= partial derivative) in the node is transferred to next node

5.3 Backpropagation

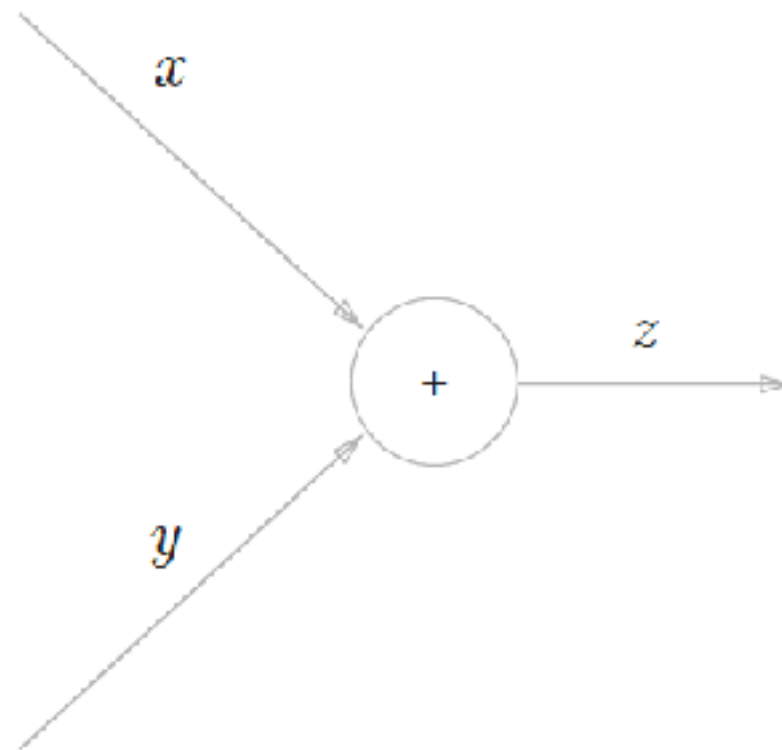
- Backward propagation in ***addition*** node

When

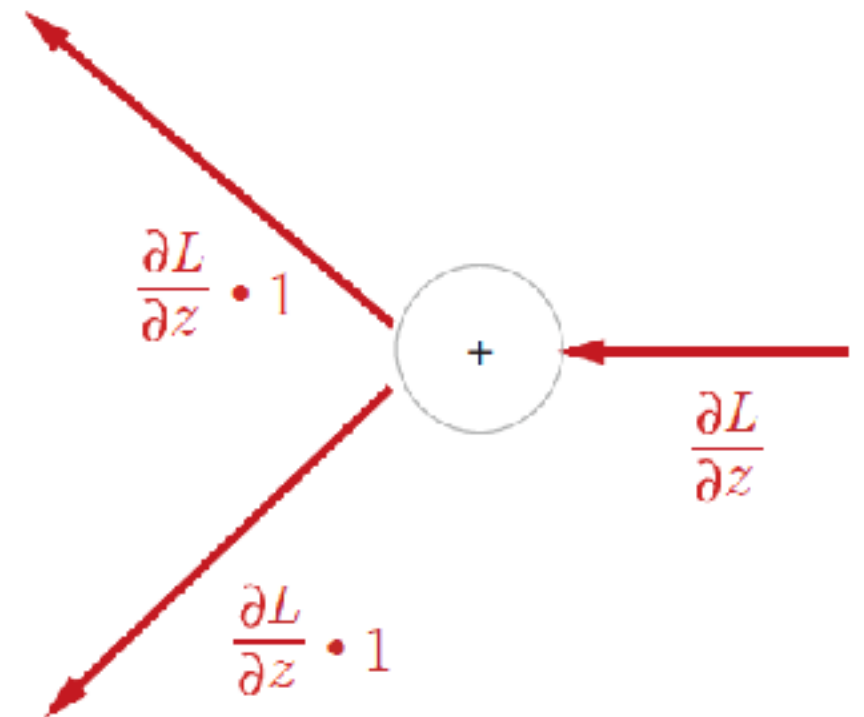
$$z = x + y$$

$$\frac{\partial z}{\partial x} = 1$$

$$\frac{\partial z}{\partial y} = 1$$



Forward propagation



Backward propagation

=> merely transfer input to output as intact

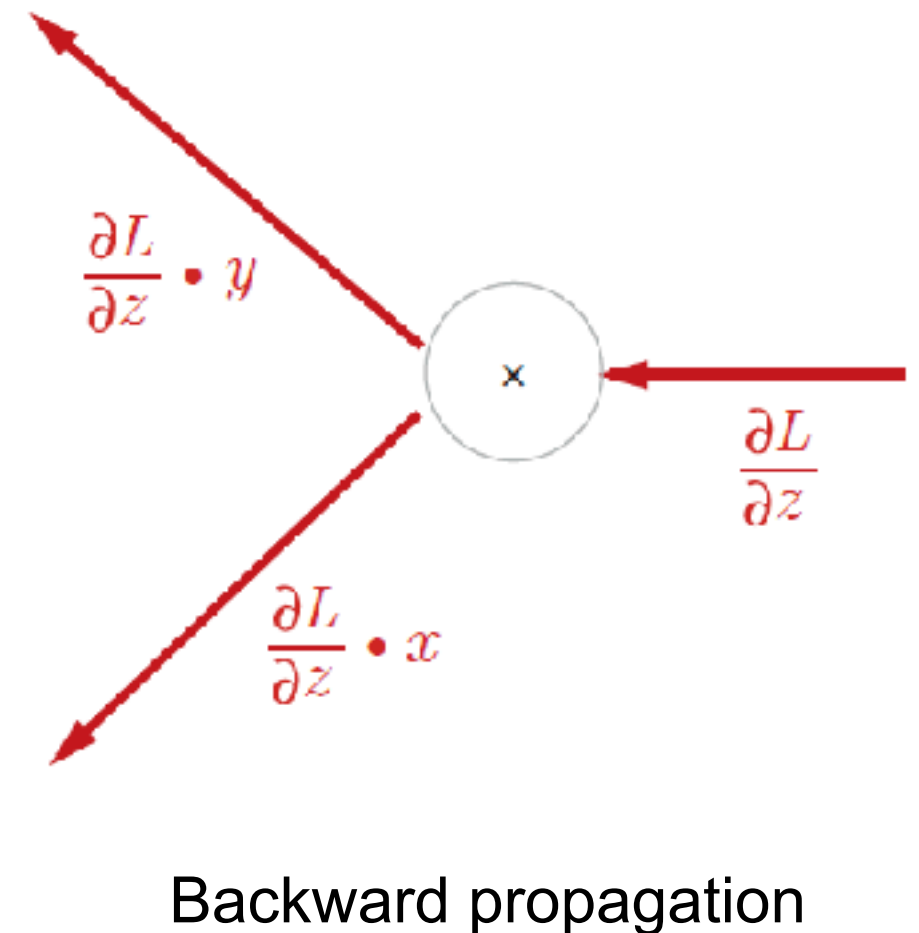
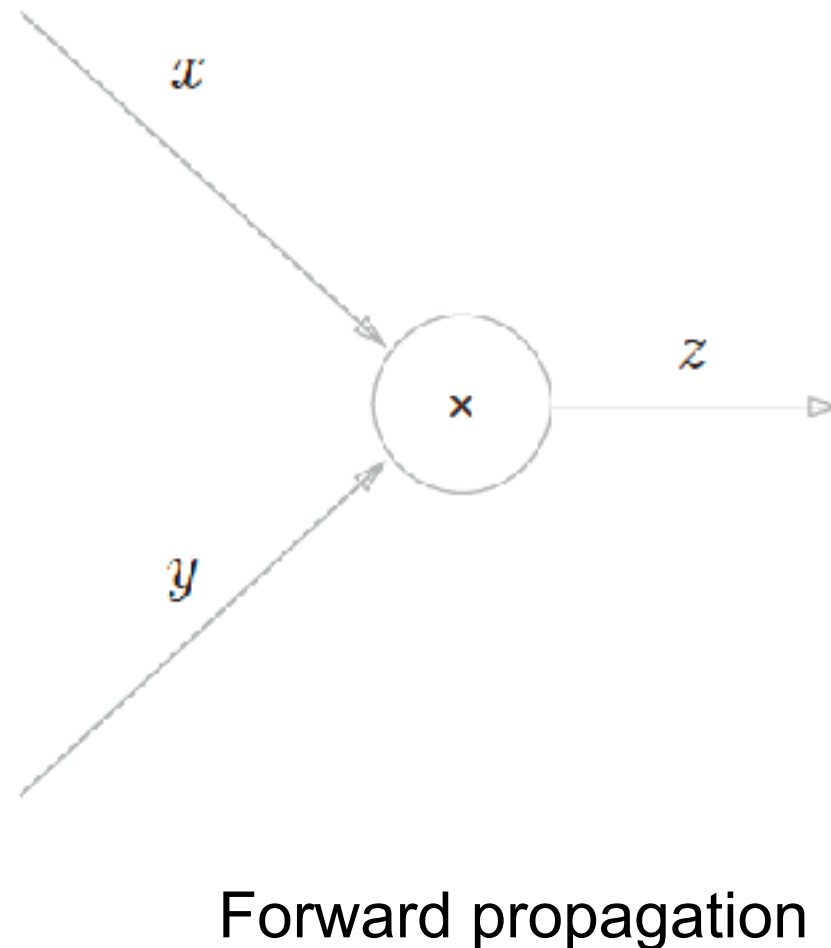
- Backward propagation in ***multiplication*** node

When

$$z = xy$$

$$\frac{\partial z}{\partial x} = y$$

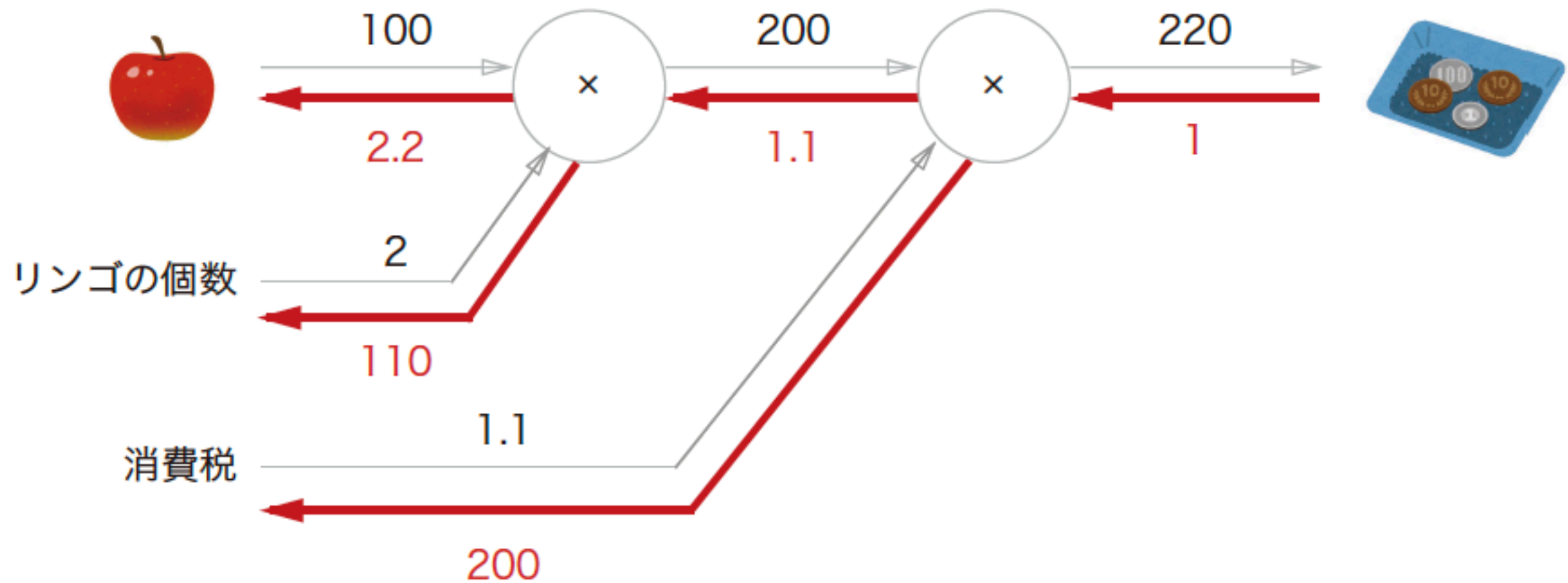
$$\frac{\partial z}{\partial y} = x$$



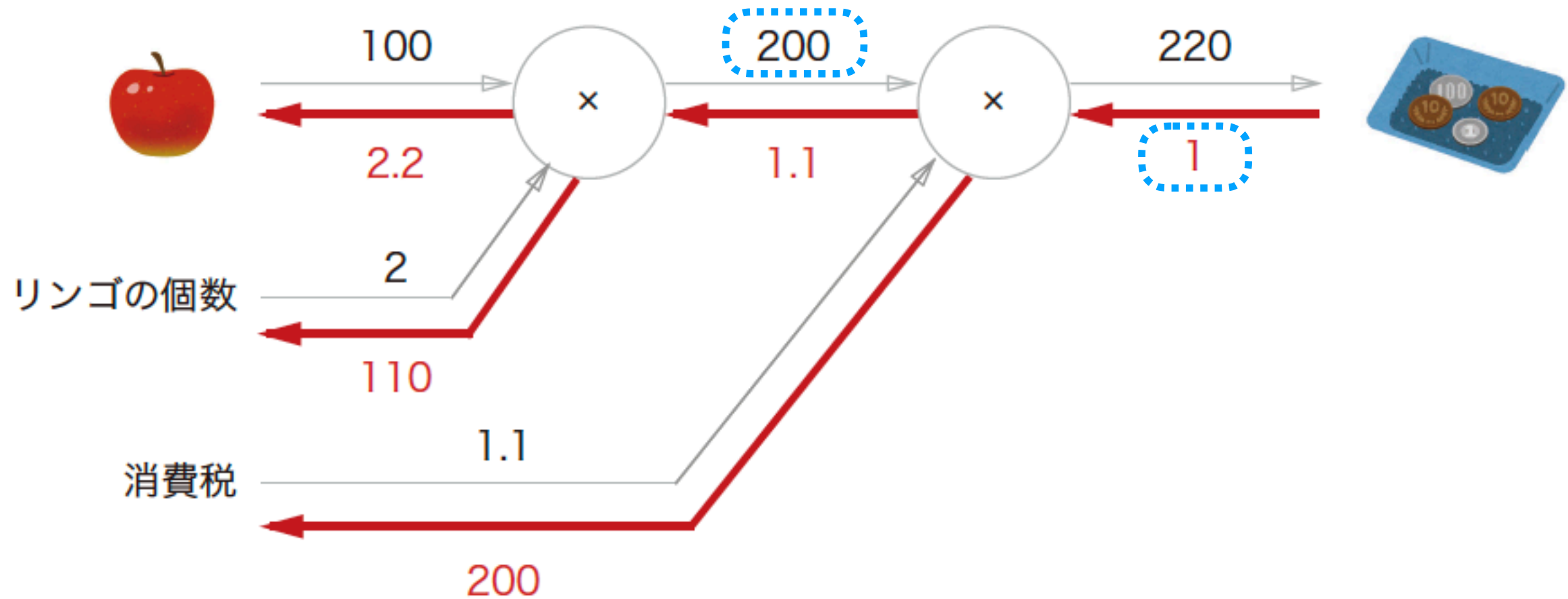
Backpropagation of multiplication needs to the value of input signals
(at forward propagation)

=> Thus, implementation of multiplication node require holding the input value

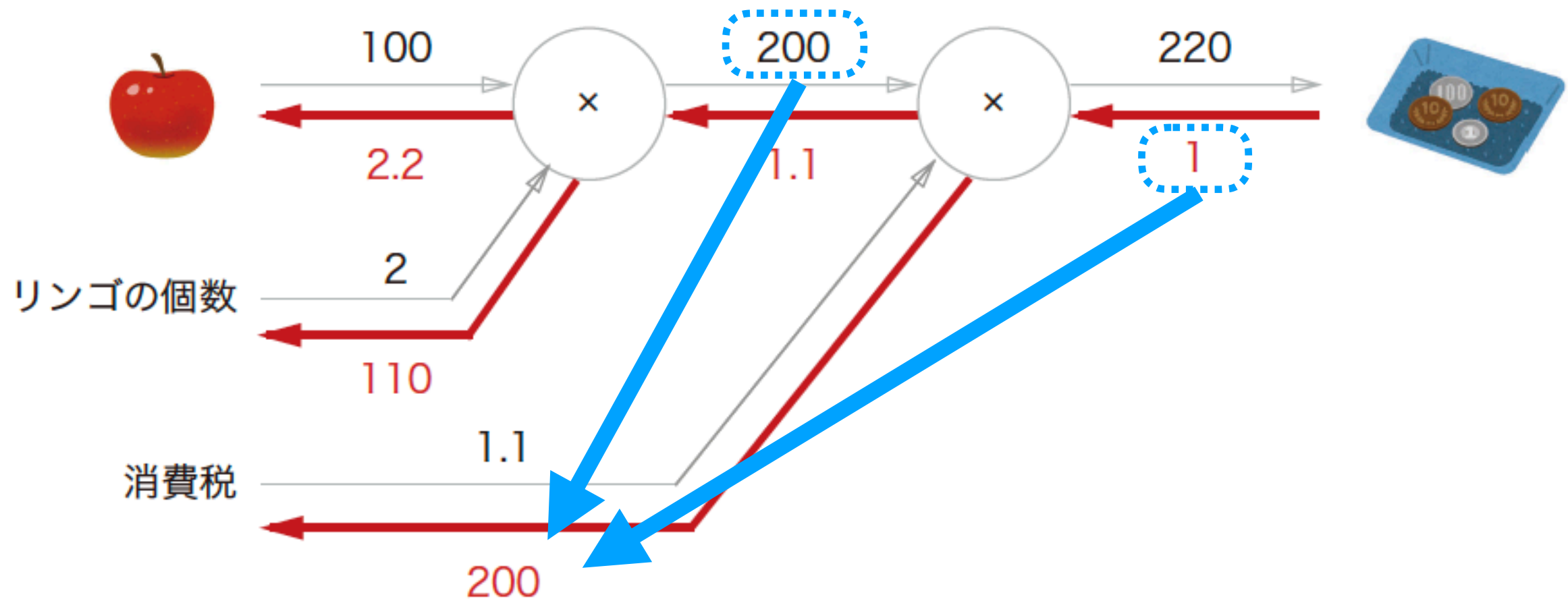
Example: Paid for apple



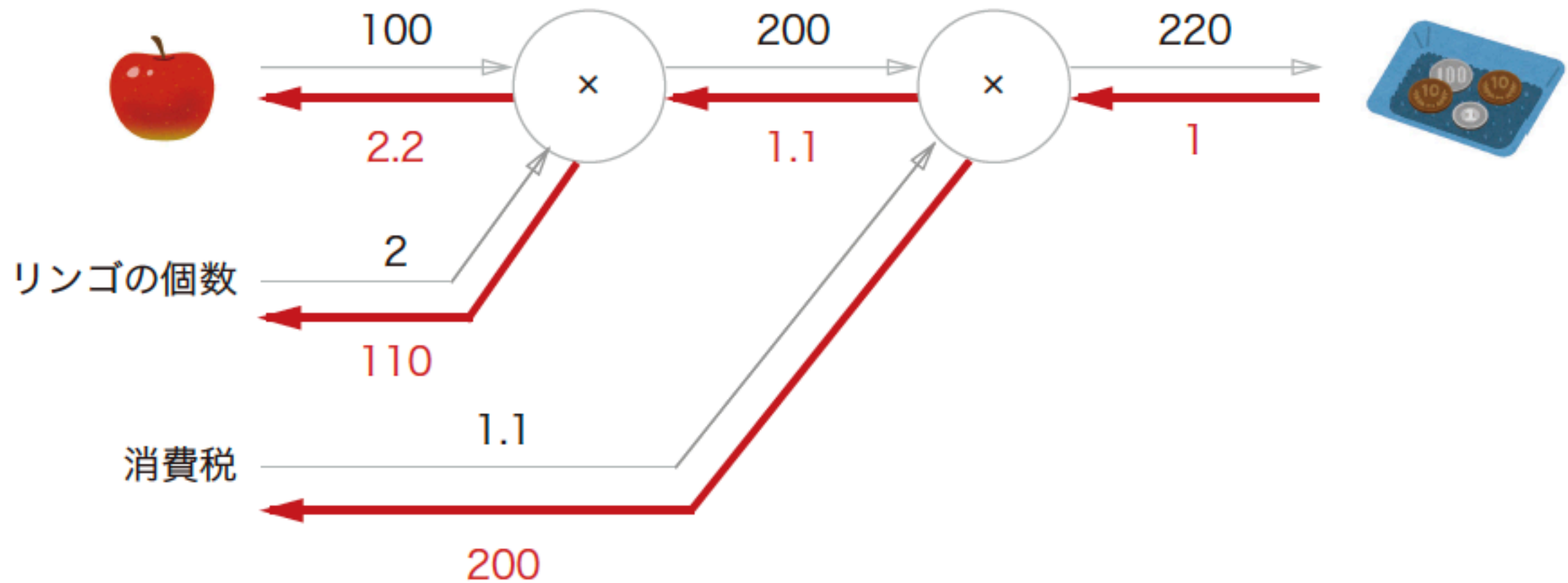
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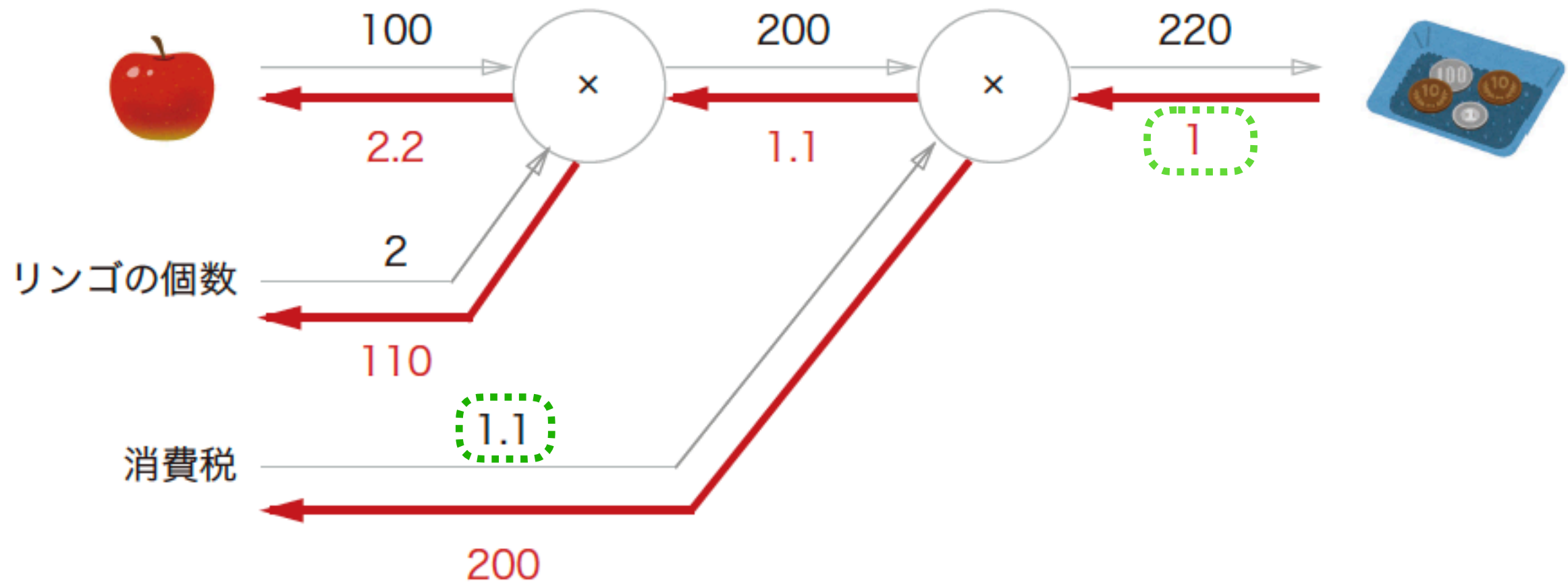
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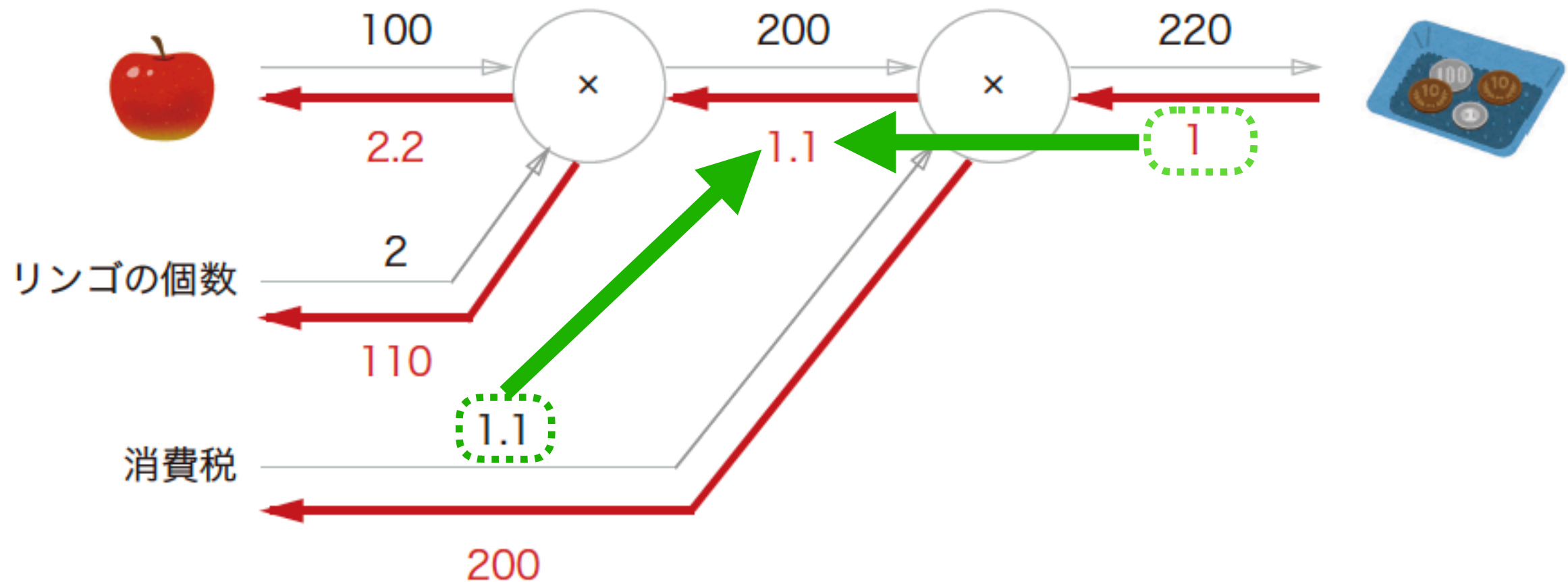
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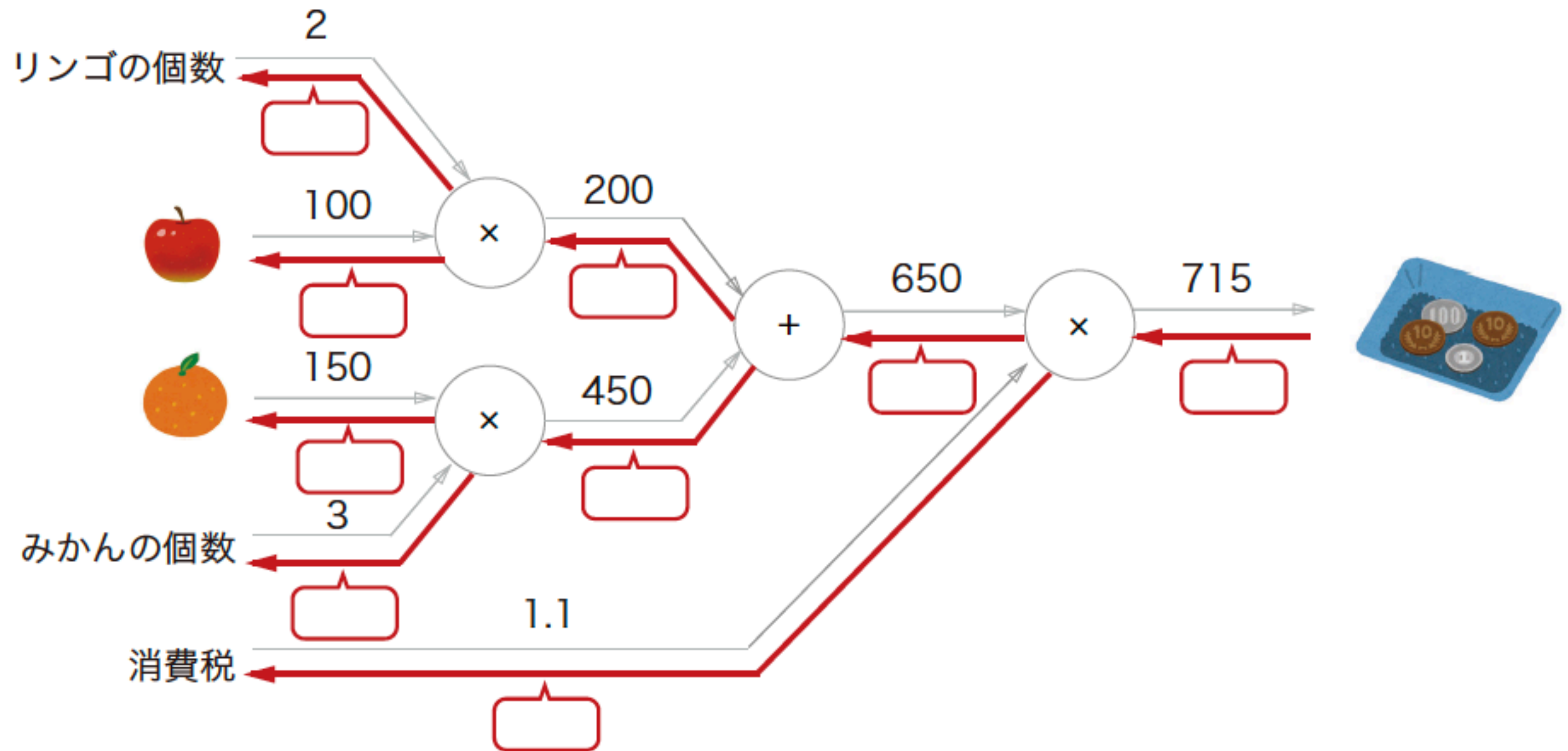
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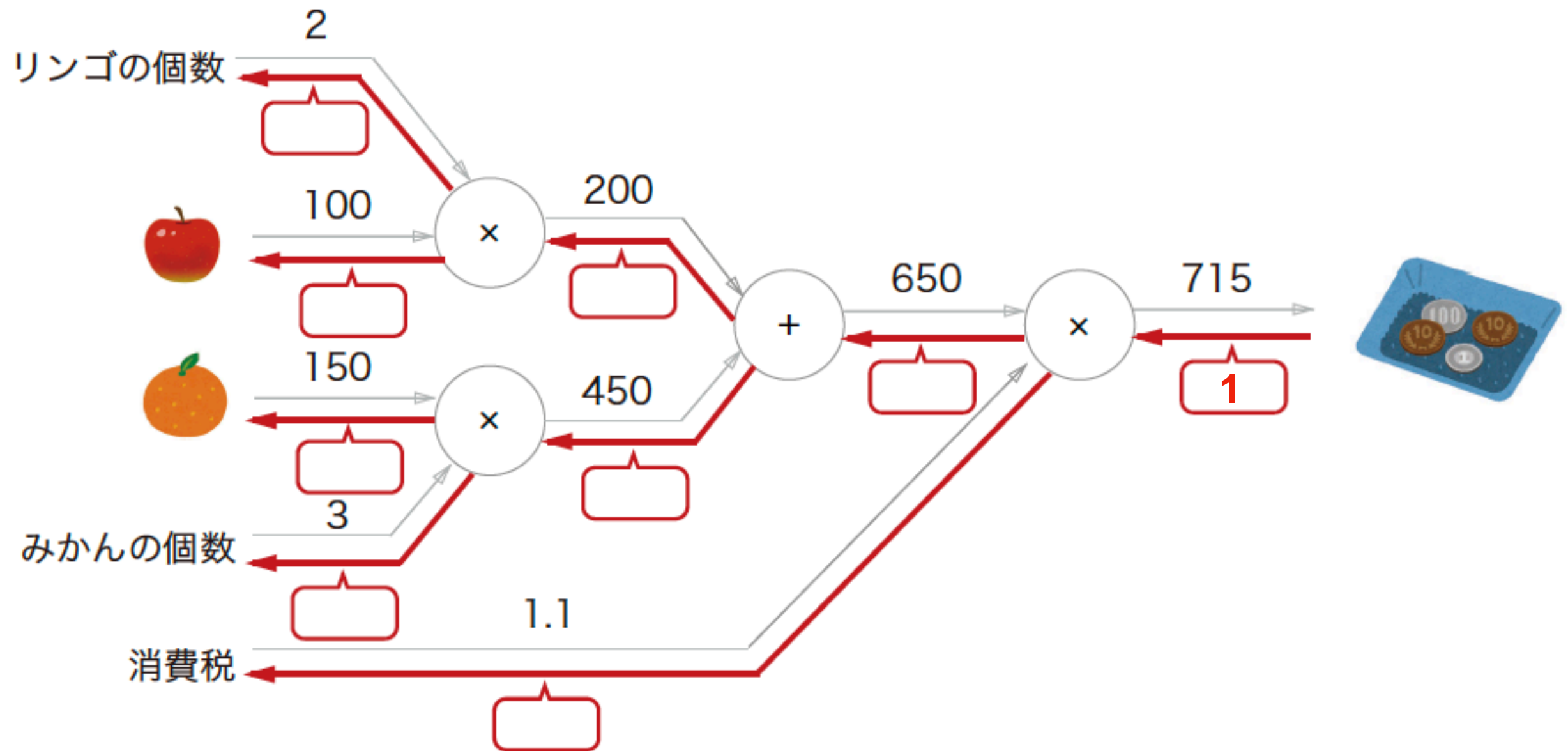
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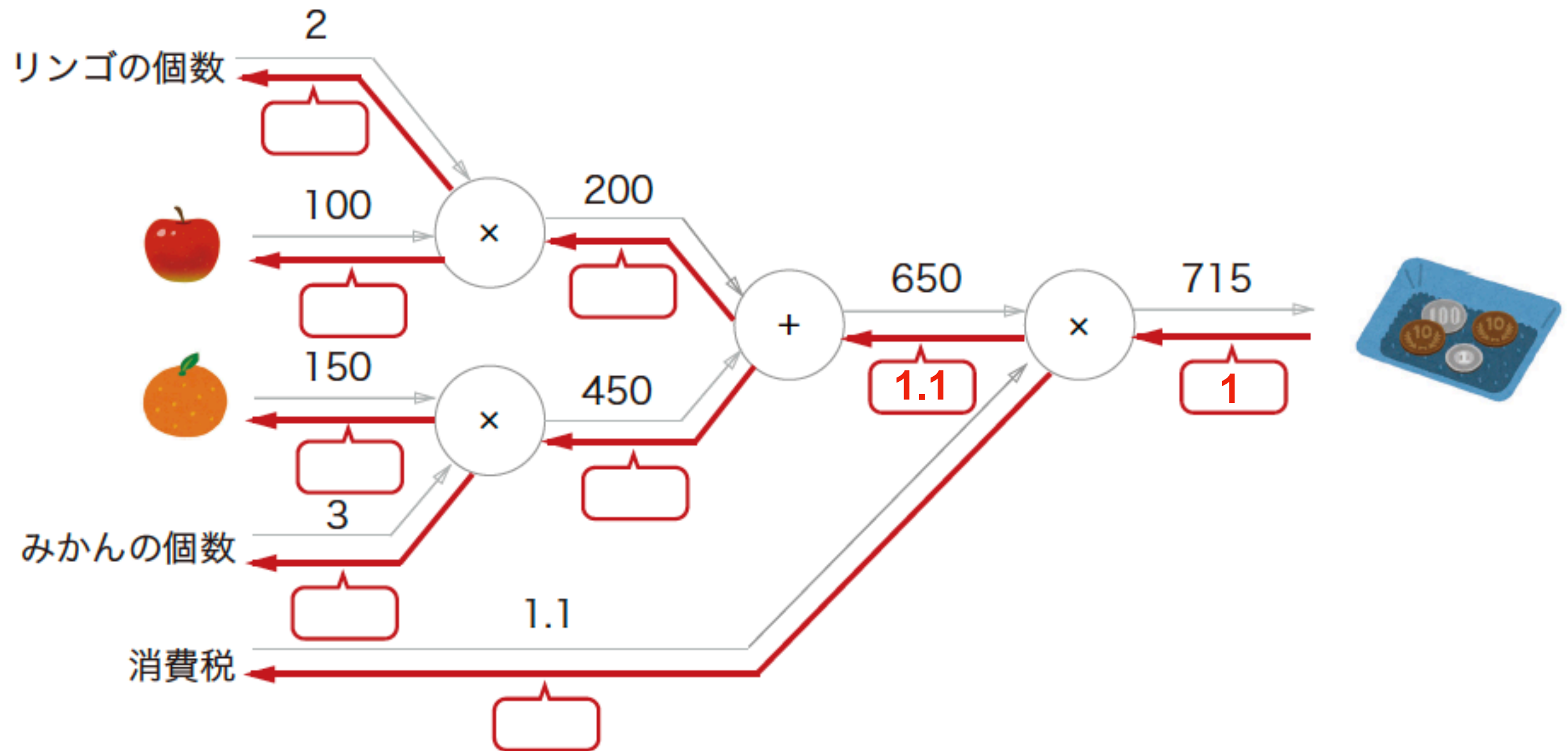
Practice: Apples and Oranges



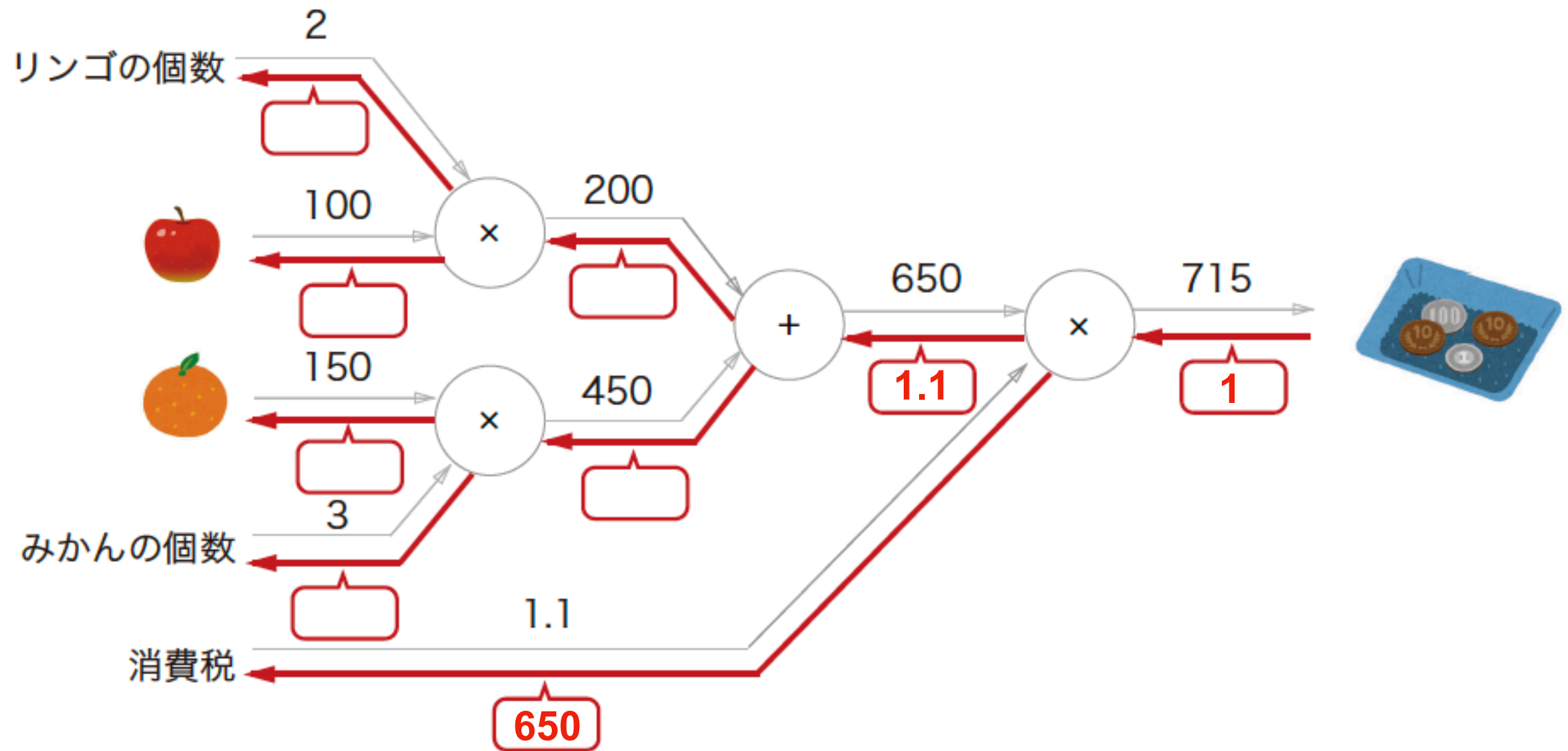
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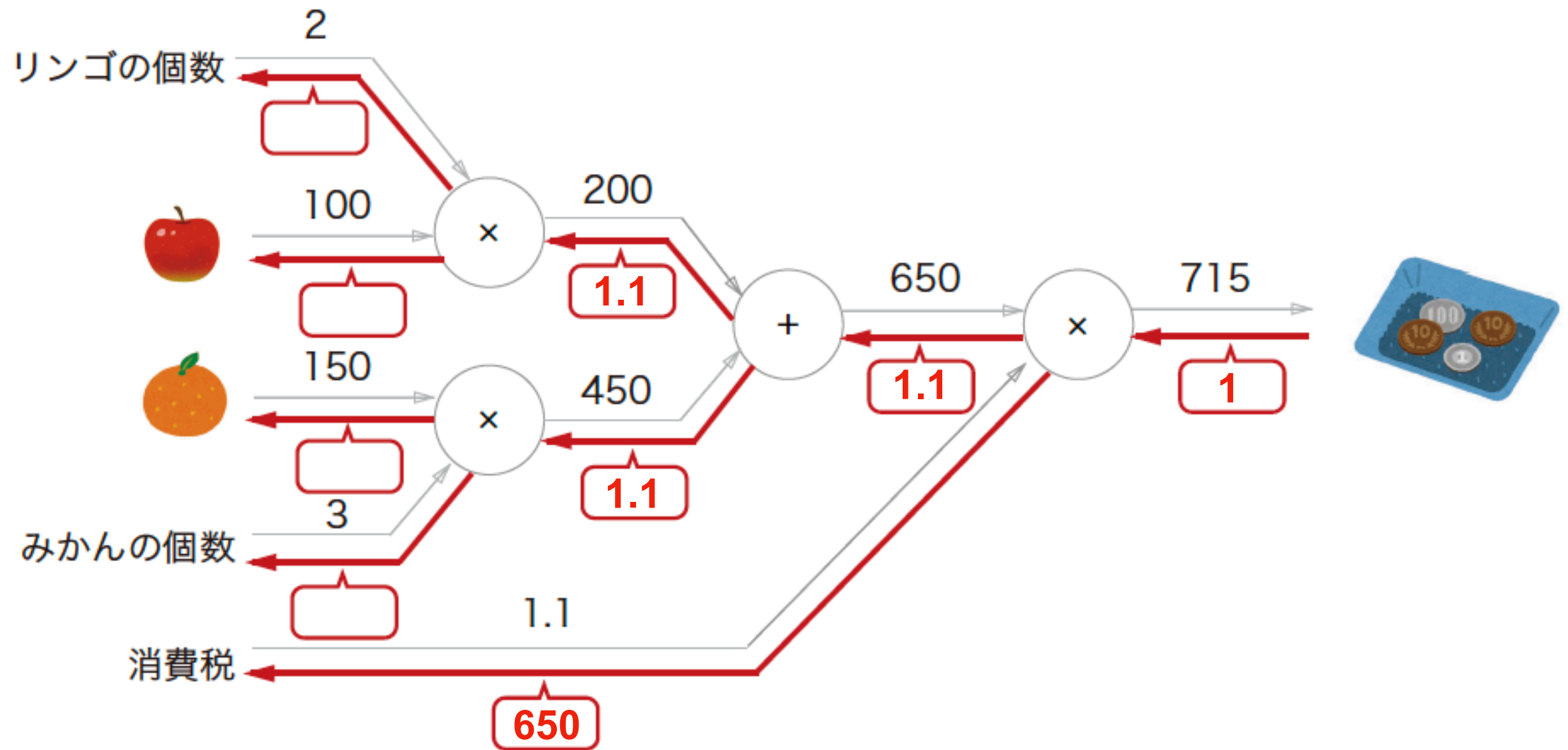
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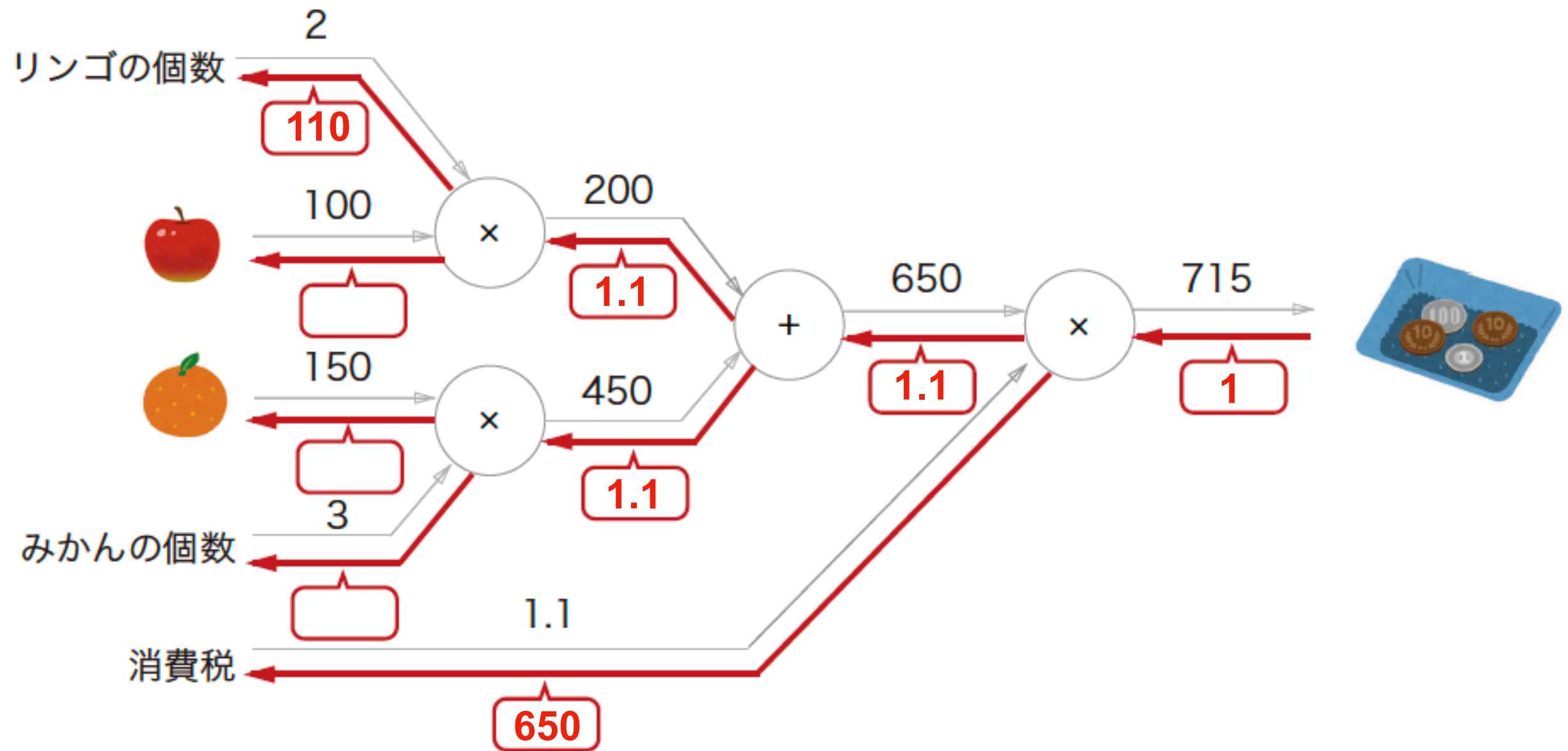
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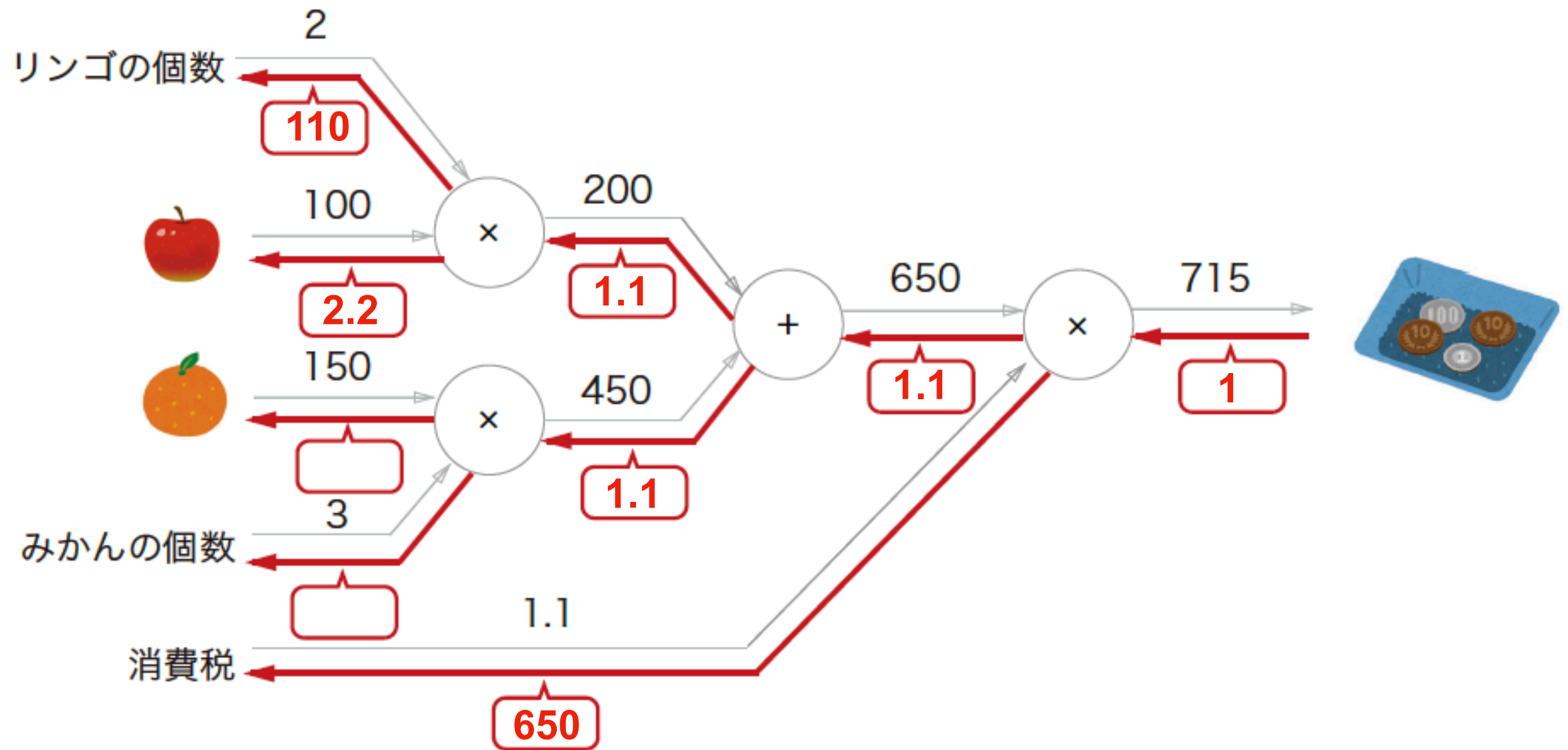
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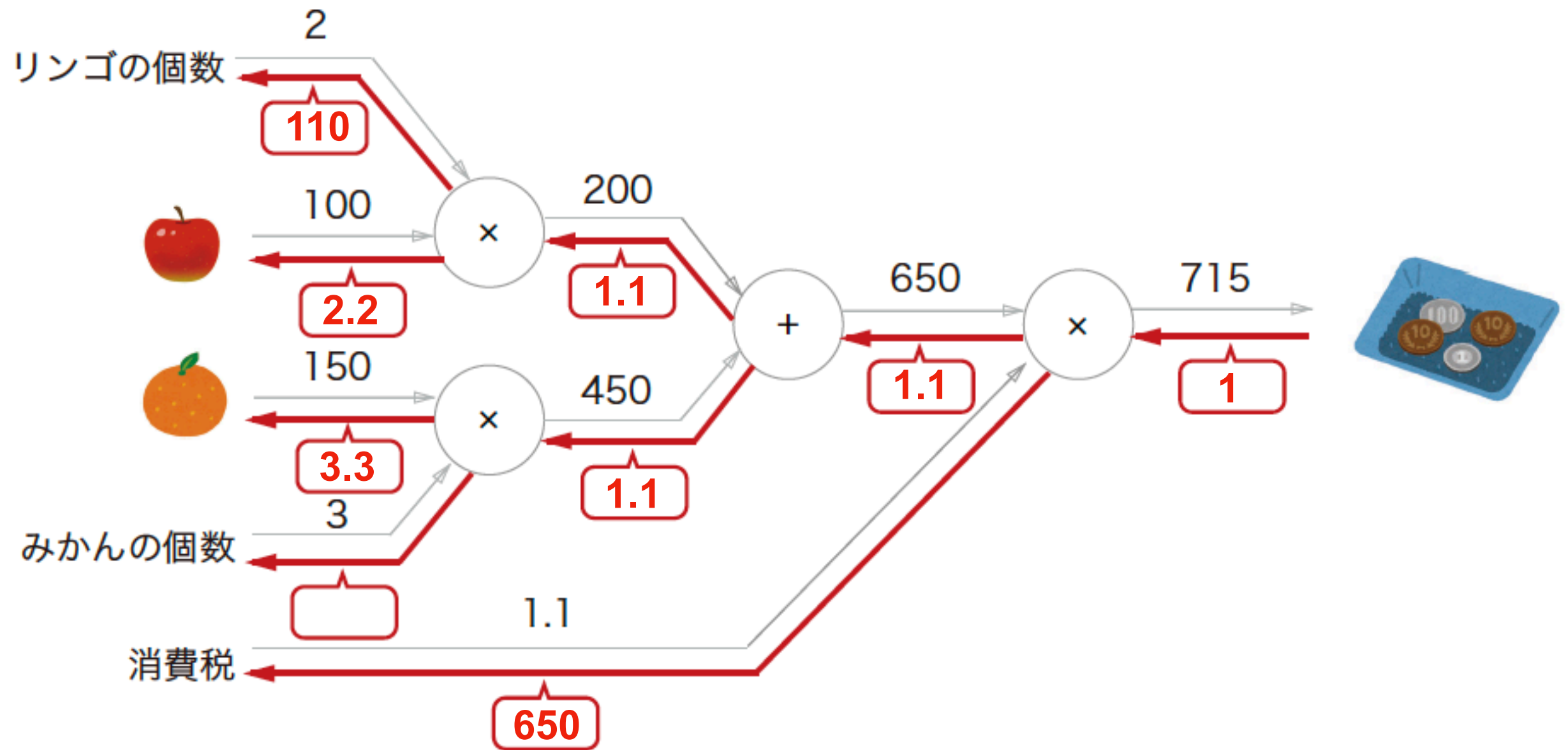
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Practice: Apples and Oranges



The diagram illustrates a calculation process for fruit prices. It starts with three inputs on the left: 'リンゴの個数' (Number of Apples) with value 2, 'みかんの個数' (Number of Oranges) with value 3, and '消費税' (Consumption Tax) with value 1.1. These inputs feed into three intermediate calculation nodes (circles with 'x' or '+'). The first 'x' node calculates 2 * 100 = 200. The second 'x' node calculates 3 * 150 = 450. The '+' node calculates 200 + 450 = 650. The final 'x' node calculates 650 * 1.1 = 715. Red arrows and callouts highlight specific values and their relationships: 110 (2 * 55), 2.2 (100 * 2.2), 3.3 (150 * 3.3), 1.1 (tax rate), 165 (3 * 55), 650 (sum of 200 and 450), and 1 (tax multiplier). The final output is 715, shown next to an illustration of a blue box containing coins (100, 10, 1).

```
graph LR; A[リンゴの個数: 2] --> X1((x)); B[みかんの個数: 3] --> X2((x)); C[消費税: 1.1] --> P1((+)); D[100] --> X1; E[150] --> X2; X1 -- 200 --> P1; X2 -- 450 --> P1; P1 -- 650 --> X3((x)); C -- 1.1 --> X3; X3 -- 715 --> F[715];
```

