

April 19-20, 2019
Computer History Museum
Mountain View, CA

Secure and Privacy-preserving Computation

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Recent Breaches

500 million records containing personal information of guests

The screenshot shows the FTC Consumer Information website. At the top, there are two large circular seals: one for the FTC and one for the U.S. Department of Justice. Below the seals, the text "FEDERAL TRADE COMMISSION" and "Consumer Information" is displayed. A navigation bar at the bottom includes links for "MONEY & CREDIT", "HOMES & MORTGAGES", "HEALTH & FITNESS", "JOBS & MAKING MONEY", and "PRIVACY, IDENTIT[...]".

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The Marriott data breach

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December 4, 2018
by Seena Gressin
Attorney, Division of Consumer & Business Education, FTC

Marriott International says that a breach of its Starwood guest reservation database exposed the personal information of up to 500 million people. If your information was exposed, there are steps you can take to help guard against its misuse.

143 million records containing personal information of consumers

The screenshot shows the FTC Consumer Information website. At the top, there are two large circular seals: one for the FTC and one for the U.S. Department of Justice. Below the seals, the text "FEDERAL TRADE COMMISSION" and "Consumer Information" is displayed. A navigation bar at the bottom includes links for "MONEY & CREDIT", "HOMES & MORTGAGES", "HEALTH & FITNESS", "JOBS & MAKING MONEY", and "PRIVACY, IDENTIT[...]".

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The Equifax Data Breach: What to Do

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September 8, 2017
by Seena Gressin
Attorney, Division of Consumer & Business Education, FTC

If you have a [credit report](#), there's a good chance that you're one of the 143 million American consumers whose sensitive personal information was exposed in a data breach at Equifax, one of the nation's three major credit reporting agencies.

Privacy Related Regulations

- Europe:
 - GDPR: General Data Protection Regulation
- North America:
 - FCRA: Fair Credit Reporting Act
 - ECPA: Electronic Communications Privacy Act
 - HIPPA: Health Insurance Portability and Accountability Act

The screenshot shows a Forbes article from March 14, 2019. The title is "Data Protection Trends: What GDPR And Other Regulations Mean For 2019 And Beyond". The author is Ari Levenfeld, a Quantcast Brand Contributor. The article discusses how the effects of 2018 on privacy continue to play a significant role, particularly in the introduction of new laws and regulations to provide consumers with greater control over their personal data. The URL of the article is <https://www.forbes.com/sites/quantcast/2019/03/14/data-protection-trends-what-gdpr-and-other-regulations-mean-for-2019-and-beyond/#6b018d22728d>.

HIPAA AND COMPLIANCE NEWS

How the Federal Data Privacy Debate, Regulations May Impact Healthcare

The data privacy debate is picking up speed in Congress, and while a bipartisan bill may not pass for some time, there are common data themes for which healthcare should take notice.



<https://healthitsecurity.com/news/how-the-federal-data-privacy-debate-regulations-may-impact-healthcare>

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Privacy vs Utility

- Do we have to give up our data to get utility online (e.g., personalized recommendations, credit scores, loyalty points)?
- Secure and privacy-preserving computation techniques give us the best of both worlds (**simultaneously**), privacy and security AND utility

Full Privacy &
No Utility

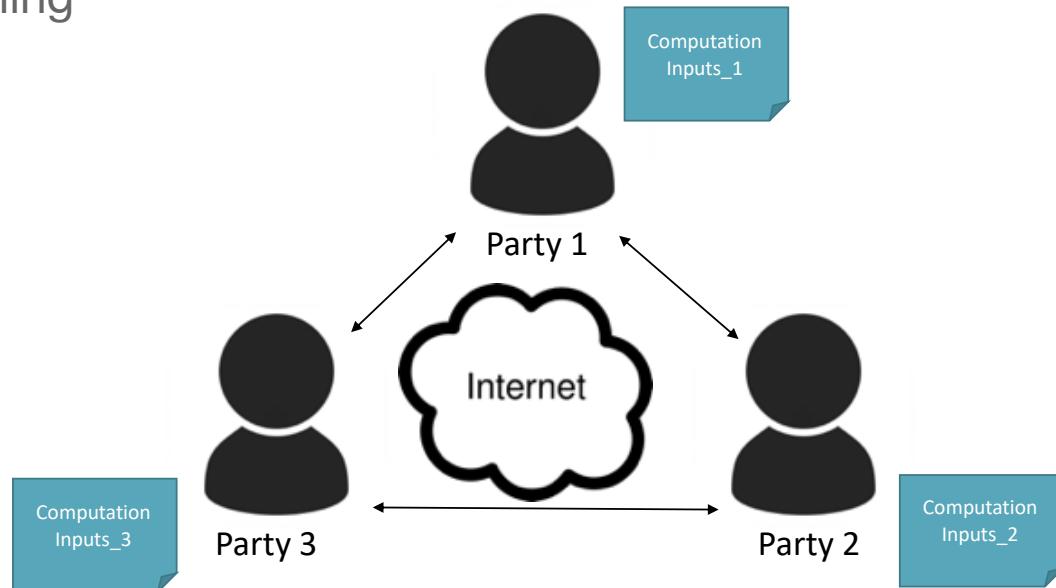
Privacy & Utility Enabled
by Secure and Privacy-
preserving Computation

Full Utility &
No Privacy



Secure Multi-Party Computation (MPC)

- MPC enables two or more (distrusting) parties to compute without revealing their data.



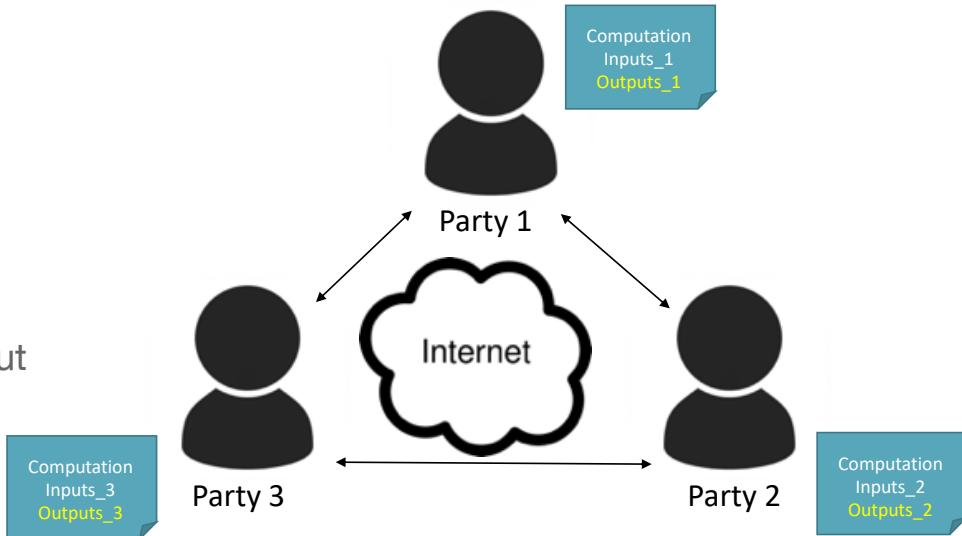
Secure Multi-Party Computation (MPC)

- MPC enables two or more (distrusting) parties to compute without revealing their data.

- Two security models:

- **Semi-honest (honest-but-curious):** parties do not modify software (follow protocol) but try to learn more information and violate privacy

- **Malicious:** parties modify software (do not follow protocol) and can misbehave and cheat



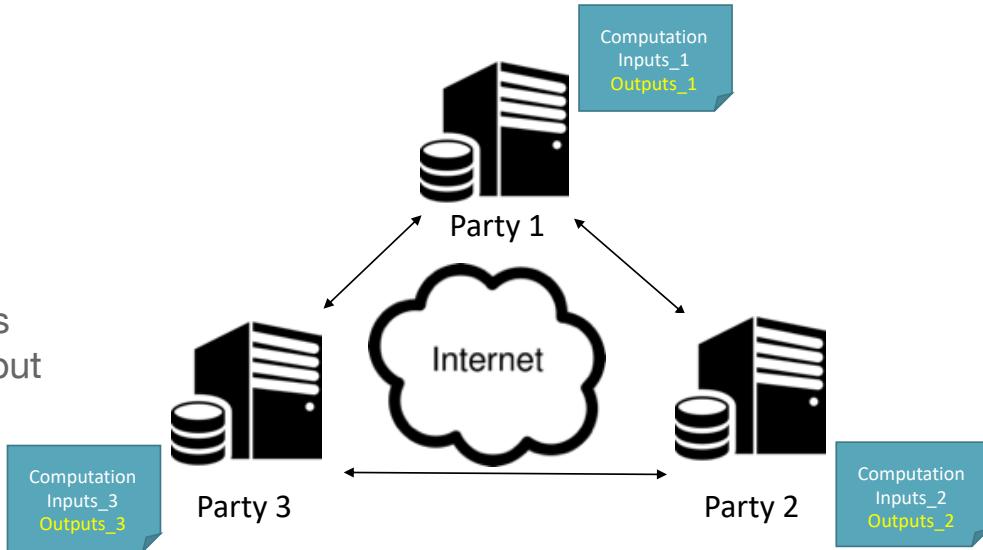
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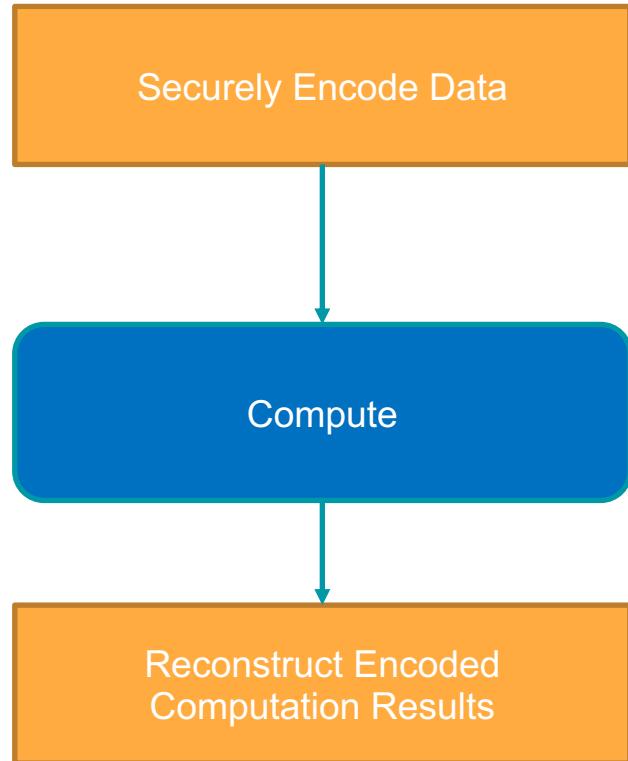
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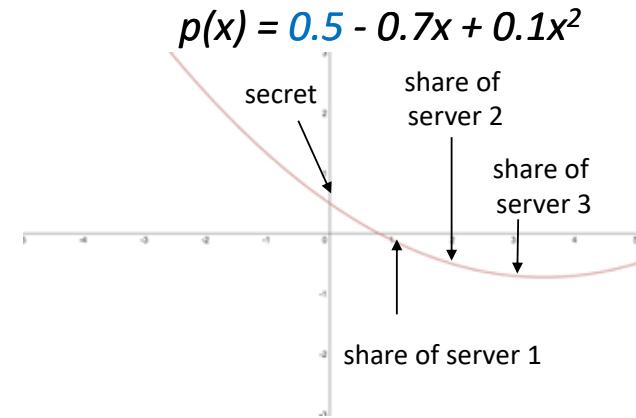
Blueprint for MPC

- Encode data into a (secure) distributed format
 - e.g., using the share algorithm in a secret sharing scheme
- Perform computation on securely encoded distributed data
- Reconstruct encoded results
 - e.g., using the reconstruct algorithm in a secret sharing scheme



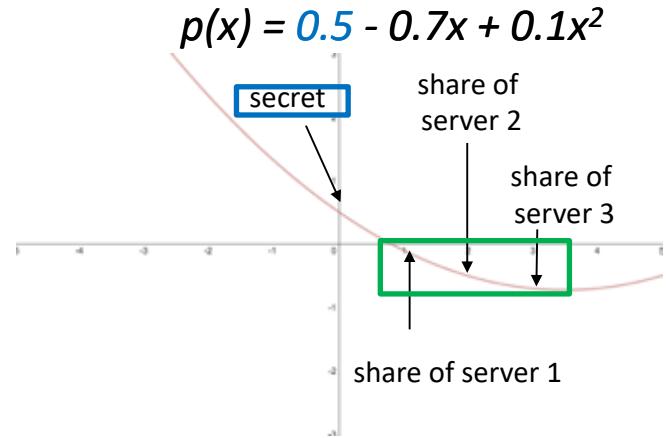
Encoding Data via Secret Sharing

- **Shamir's Technique:** assuming n parties store **secret** in constant term of degree t polynomial to tolerate up to t leaked shares (called $t+1$ out of n)
- Need two algorithms:
 - Share:** for secret s , pick random coefficients $a_1 \dots a_t$ & set $a_0 = s$ $p(x) = a_0 + a_1x + a_2x^2 + \dots + a_tx^t$ distribute shares as $p(1), p(2) \dots p(n)$ to the n servers
 - Reconstruct:** from $p(1), p(2) \dots p(t+1)$ interpolate $p(x)$ and recover secret as $p(0) = a_0 = s$



Secret Sharing: Share Algorithm

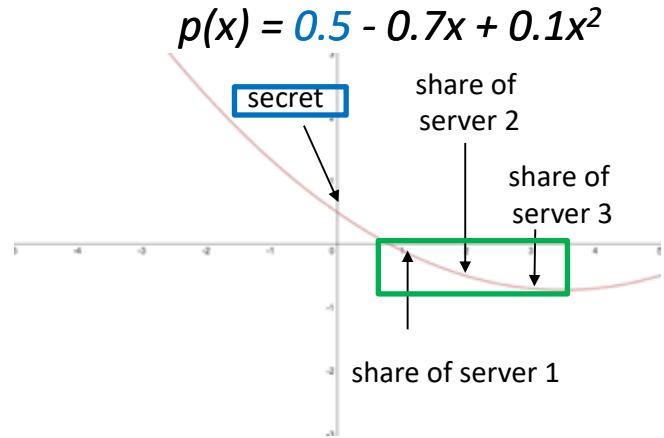
```
1 import string
2
3 from six import integer_types
4 from utilitybelt import int_to_charset, charset_to_int, base58_chars, \
5     base32_chars, zbase32_chars
6 from .primes import get_large_enough_prime
7 from .polynomials import random_polynomial, \
8     get_polynomial_points, modular_lagrange_interpolation
9
10
11
12 def share_secret secret_int, point_threshold, num_points, prime=None:
13     """ Split a secret (integer) into shares (pair of integers / x,y coords).
14         Sample the points of a random polynomial with the y intercept equal to
15         the secret int.
16     """
17
18     if point_threshold < 2:
19         raise ValueError("Threshold must be >= 2.")
20     if point_threshold > num_points:
21         raise ValueError("Threshold must be < the total number of points.")
22     if not prime:
23         prime = get_large_enough_prime([secret_int, num_points])
24     if not prime:
25         raise ValueError("Error! Secret is too long for share calculation!")
26     coefficients = random_polynomial(point_threshold-1, secret_int, prime)
27     points = get_polynomial_points(coefficients, num_points, prime)
28
29     return points
```



Share algorithm in code sample called:
`share_secret(...)`

Secret Sharing: Reconstruct Algorithm

```
32
33
34 def reconstruct_secret(points, prime=None):
35     """ Join int points into a secret int.
36     Get the intercept of a random polynomial defined by the given points.
37     """
38
39     if not isinstance(points, list):
40         raise ValueError("Points must be in list form.")
41     for point in points:
42         if not isinstance(point, tuple) and len(point) == 2:
43             raise ValueError("Each point must be a tuple of two values.")
44         if not (isinstance(point[0], integer_types) and
45                 isinstance(point[1], integer_types)):
46             raise ValueError("Each value in the point must be an int.")
47     x_values, y_values = zip(*points)
48     if not prime:
49         prime = get_large_enough_prime(y_values)
50     free_coefficient = modular_lagrange_interpolation(0, points, prime)
51     secret_int = free_coefficient # the secret int is the free coefficient
52
return secret_int
```



Reconstruct algorithm in code sample called:
`reconstruct_secret(...)`

Source code sample from: <https://github.com/blockstack/secret-sharing>

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Blueprint for MPC

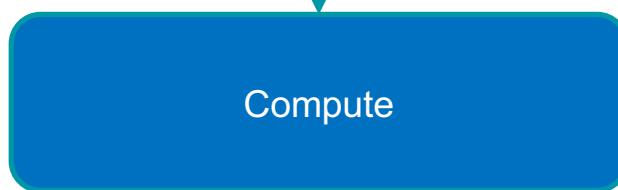
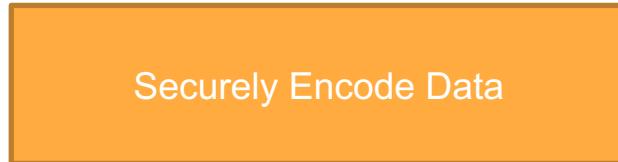
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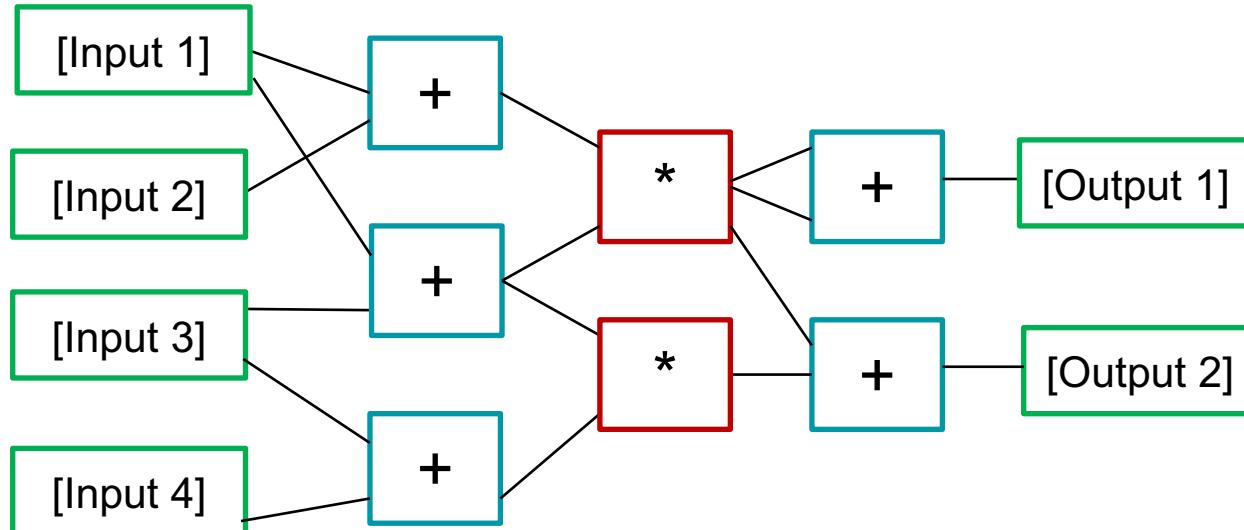
- e.g., using the reconstruct algorithm in a secret sharing scheme



NEXT

Computing Using Secret Shared Data

- One way to implement MPC
- Computation represented as an arithmetic circuit
- Circuit consists of **addition** and **multiplication** of secret shares
- [Input X] denotes secret sharing of Input X



Realizing Computation Gates

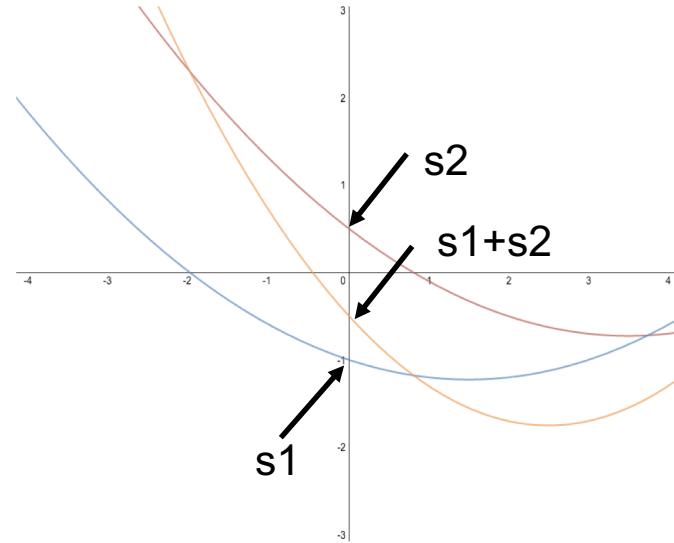
- **Addition:** $[s_1] + [s_2] = [s_1+s_2]$

if $f_1(x) = a_0 + a_1x + a_2x^2 + \dots + a_tx^t$
and $f_2(x) = b_0 + b_1x + b_2x^2 + \dots + b_tx^t$
then

$$f_1(x) + f_2(x) = (a_0 + b_0) + (a_1 + b_1)x + \dots + (a_t + b_t)x^t$$

- **Multiplication:** resulting polynomial has double degree!

$$f_1(x) * f_2(x) = (a_0 b_0) + (b_0 a_1 + a_0 b_1)x + \dots + (a_t b_t)x^{2t}$$

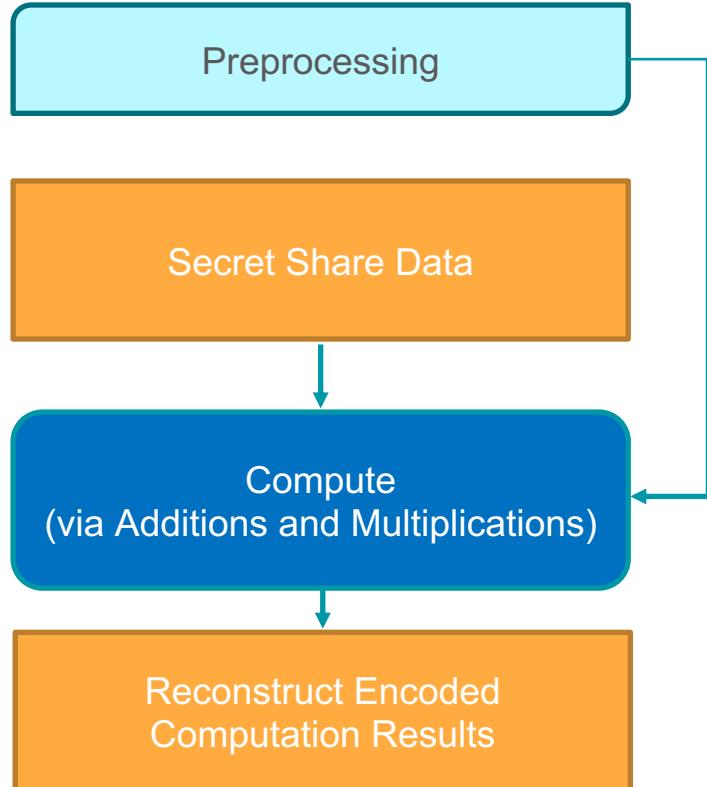


How to Multiply Using Pre-computation

- Generate random triples (a, b, c) such that $c = a * b$ and share them $([a], [b], [c])$
- To multiply two shares $[s_1]$ and $[s_2]$ each server computes:
 - $[s_1 - a]$ and reveals it $i = \text{reconstruct}([s_1 - a])$
 - $[s_2 - b]$ and reveals it $k = \text{reconstruct}([s_2 - b])$
 - Servers compute their share of the product $[s_1] * [s_2] = i * k + i * [b] + k * [a] + [c]$
 - Why it works:
$$(s_1 - a) * (s_2 - b) + (s_1 - a) * b + (s_2 - b) * a + a * b =$$
$$s_1 * s_2 - a * s_2 - b * s_1 + a * b + b * s_1 - a * b + a * s_2 - a * b + a * b =$$
$$s_1 * s_2$$

Recap of MPC's Operation

- Preprocessing to set up some parameters (e.g., multiplication triples)
- Parties **secret share** their data
- Parties **compute (via additions and multiplications)** on the secret shared data
- Parties **reconstruct** the result of the computation



Putting It All Together

- Implementing a basic MPC class using the Charm library
- Charm is a Python framework for rapidly prototyping advanced cryptographic protocols and primitives
- <https://github.com/JHUISI/charm>

Note: sending shares to other parties in mpcReconstruct() is left out, this code assumes all shares are already received.

```
1  from charm.toolbox.pairinggroup import PairingGroup,ZR,order
2  from charm.toolbox.secretshare import *
3
4  class MPC:
5
6      def __init__(self, threshold, num_parties, field_size):
7          self.num_parties = int(num_parties)
8          self.threshold = int(threshold)
9          self.field_size = field_size # for now will only use 512 bits
10         self.field = ...PairingGroup('SS512')
11         self.ssObject = SecretShare(self.field, verbose_status=True)
12
13
14     def mpcShare(self, ip_to_share):
15         print(self.threshold)
16         print(type(self.num_parties))
17         shares = self.ssObject.genShares(ip_to_share, self.threshold, self.num_parties)
18         return shares
19
20
21     # Function to add shares (assumed to be given in a list)
22     def mpcAdd(self, inputs):
23         sum = self.field.init(ZR, 0)
24         print('Placeholder for mpcAdd function.\n')
25         for i in range(0, len(inputs)):
26             sum += inputs[i]
27
28         return sum
29
30
31     def mpcMult(self, shares):
32         print('Placeholder for mpcMult function.\n')
33         return
34
35
36     def mpcReconstruct(self, shares):
37         print('Placeholder for recon function.\n')
38         print(shares)
39         dictionary_points={}
40         for i in range(1, self.num_parties+1):
41             dictionary_points[self.field.init(ZR, i)]=shares[i]
42
43         recoveredSecret=self.ssObject.recoverSecret(dictionary_points)
44
45         return recoveredSecret
```



Multiplication Algorithm Pseudocode

- Assuming that a random triple (a, b, c) where $c=a^*b$ is generated as part of the setup
- Each party gets a share of the triple (a, b, c) , i.e., $([a], [b], [c])$
- Recall that the product is:
$$(s_1 - a)^*(s_2 - b) + (s_1 - a)^*b + (s_2 - b)^*a + a^*b$$

Note: sending shares to other parties in `mpcReconstruct()` is left out, this code assumes all shares are already received.

```
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53

# Function to multiply shares (assumed to be given in a list)
def mpcMult(self, shares, triple):
    print('Placeholder for mpcMult function.\n')

    s1 = shares[0]
    s2 = shares[1]

    a = triple[0]
    b = triple[1]
    c = triple[2]

    tmp1 = self.mpcAdd([s1, -a])
    tmp2 = self.mpcAdd([s2, -b])

    i = self.mpcReconstruct(tmp1)
    k = self.mpcReconstruct(tmp2)

    product_share = (i*k) + (i*b) + (k*a) + c

    return product_share
```

Example Open Source MPC Software

- SCALE-MAMBA: <https://github.com/KULeuven-COSIC/SCALE-MAMBA>
- Two main components to the system
 - a run time system called Secure Computation Algorithms from LEuven (SCALE)
 - a Python-like programming language called Multiparty AlgorithMs Basic Argot* (MAMBA**)
- Example on right from page 18 in documentation:
<https://homes.esat.kuleuven.be/~nsmart/SCALE/Documentation.pdf>

```
1  # (C) 2017 University of Bristol. See License.txt
2  # (C) 2018 KU Leuven. See License.txt
3
4  def test(actual, expected):
5      actual = actual.reveal()
6
7      print_ln('expected %s, got %s', expected, actual)
8      # cint: clear integers modulo p
9      # sint: secret integers modulo p
10
11     a = sint(1)
12     b = cint(2)
13
14     test(a + b, 3)
15     test(a + a, 2)
16     test(a * b, 2)
17     test(a * a, 1)
18     test(a - b, -1)
19     test(a < b, 1)
20     test(a <= b, 1)
21     test(a >= b, 0)
22     test(a > b, 0)
23     test(a == b, 0)
24     test(a != b, 1)
25     clear_a = a.reveal()
26
27     # arrays and loops
28     a = Array(100, sint)
29
30     @for_range(100)
31     def f(i):
32         a[i] = sint(i)**2
33         test(a[99], 99**2)
34
35     # conditional
36     if_then(cint(0))
37     a[0] = 123
38     else_then()
39     a[0] = 789
40     end_if()
41
42     test(a[0], 789)
```

* Argot means secret language

** MAMBA is a snake (similar to Python)

Advanced Topics

- Dealing with misbehaving parties
 - Semi-honest (honest-but-curious): do not modify software but want to violate privacy
 - Malicious model: modify software and can cheat
- Scalability:
 - Large datasets: 100s of GBs or more
 - Complex functions: machine learning, database queries, numerical analysis
 - Larger number of parties: 10s or even 100s of parties

Other Techniques

- Secure Two-party Computation
 - Specialized techniques if computation is only between two parties (e.g., two companies)
 - Suitable for cloud settings
- Fully Homomorphic Encryption
 - Suitable for cloud settings (offloading computation to the cloud), or when interaction is not desired
- Differential Privacy
 - For computing and revealing statistics over databases while preserving privacy



Summary

- Never invent your own cryptography or privacy techniques!
- We do not have to reveal data to use it in (online) computation
- Advanced cryptographic techniques are now becoming increasingly practical
- Open source frameworks and libraries are becoming mature
- More work required to improve usability for non-experts
- Starting to be used in live practical applications



Resources

- Further reading:
 - Free book overviewing different MPC techniques (the protocols):
<https://www.cs.virginia.edu/~evans/pragmaticmpc/pragmaticmpc.pdf>
 - More books, tutorials, articles and videos: <https://github.com/rdragos/awesome-mpc>
- Some mature and usable open source software for MPC:
 - Python based - SCALE-MAMBA: <https://github.com/KULeuven-COSIC/SCALE-MAMBA>
 - Java based - JIFF: <https://github.com/multiparty/jiff>



Questions

