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Big Data Analysis and Cross-Layer Optimization for Communication, Caching and Computing (C^3) Networks

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Thanks for NSF,

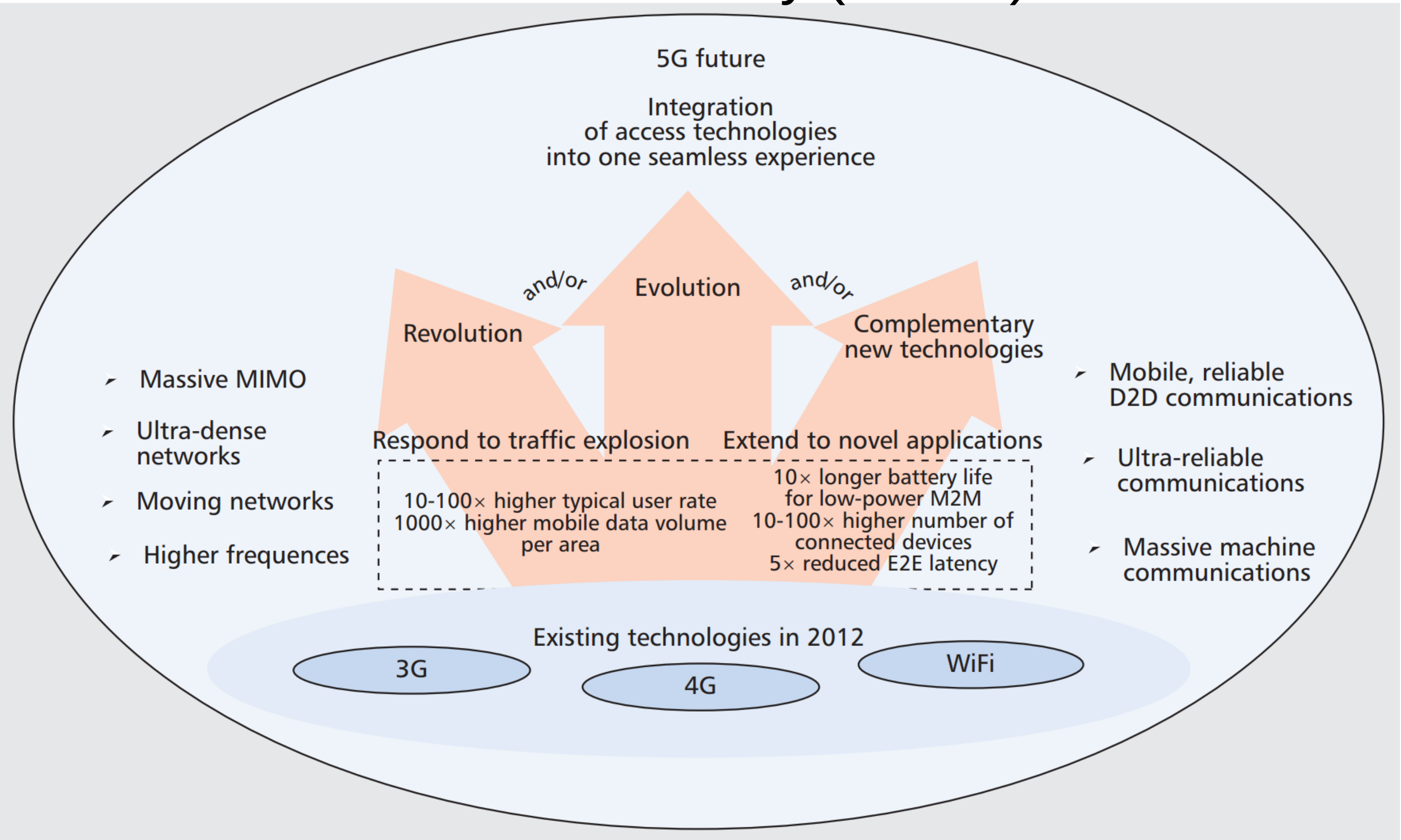
work by Ye Yu, Prof. Li Wang, Xunsheng Du and Kevin Tsai

Outline

- Introduction and Motivation for C^3 Networks
- Big Data Analysis and Cross Layer Optimization
  - Wireless Network Function Virtualization
  - Mobile Social Networks over D2D
  - Deep Learning Analysis
- Conclusions

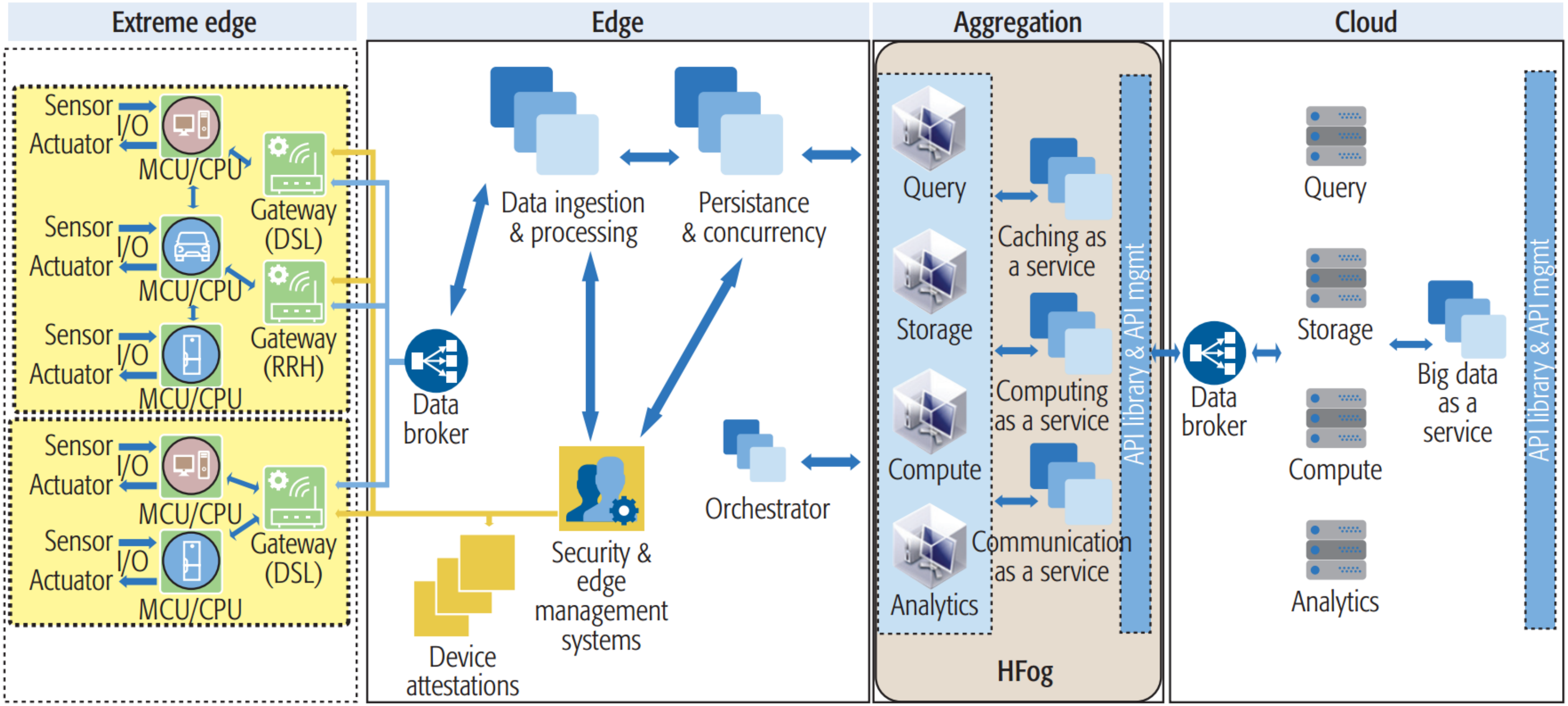
Future 5G Networks

1. Hyper-connected society
2. High data rates at the network edge (1–10 Gb/s)
3. Ultra low end-to-end latency (~1 ms).



* A. Osseiran et al., "Scenarios for 5G mobile and wireless communications: the vision of the METIS project," in IEEE Communications Magazine, vol. 52, no. 5, pp. 26-35, May 2014.

Communication, Caching and Computing



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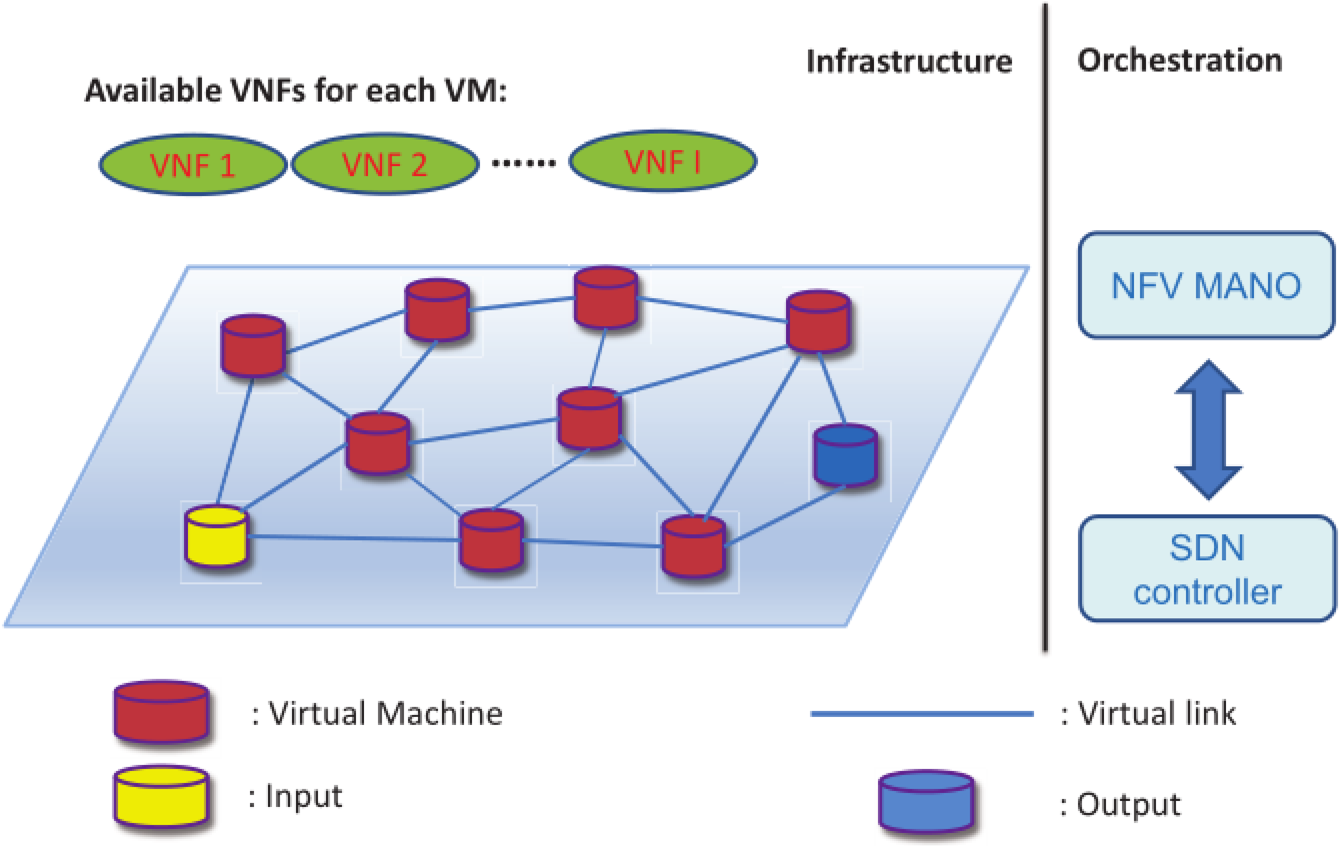
Network (Function) Virtualization

Virtualize entire classes of network node functions into building blocks that may connect, or chain together, to create communication services



Advantages

Reduce Expenditure; Accelerate Time-to-Market; Deliver Agility and Flexibility

Problem Formulation Example

$$\delta_{n,k}^{m} = \begin{cases} 1, if\ f_k^m\ is\ implemented\ on\ VM\ n \\ 0, otherwise. \end{cases}$$

number of the instances: $$e_k^m = \sum_{n=1}^{N} \delta_{n,k}^m.$$

VNF placement cost: $$Q_p = \sum_{k=1}^{K} e_k^m \xi_k^m,$$

Traffic cost: $$Q_t = \sum_{k=1}^{K} \gamma_k \sum_{n=1}^{N} v_{n,k}^m,$$

Total cost function: $$Q_{total} = Q_p + Q_t$$

Variables: $\delta_{n,k}^m$ (Integer)

$v_{n,k}^m$ (continuous)

$$\min_{\boldsymbol{\delta}^{m,(l)} \mathbf{v}^{m,(l)}} \quad Q_{total}$$

s.t $$1 \leq \sum_{n=1}^{N} \delta_{n,k}^m \leq N \quad \forall k, m,$$

VNF number

$$\sum_{k=1}^{K} \delta_{n,k}^m v_{n,k}^m \phi_k \leq C_n \quad \forall n, m,$$

VM's capacity

$$\sum_{n=1}^{N} v_{n,k}^m \geq R_k \quad \forall k,$$

Data rate requirement

$$\mu_{f_k} \leq \frac{\sum_{n=1}^{N} v_{n,k+1}^m}{\sum_{n=1}^{N} v_{n,k}^m} \quad \forall k,$$

Streaming constraint

$$\delta_{n,k}^m \in \{0, 1\} \quad \forall m, n, k.$$

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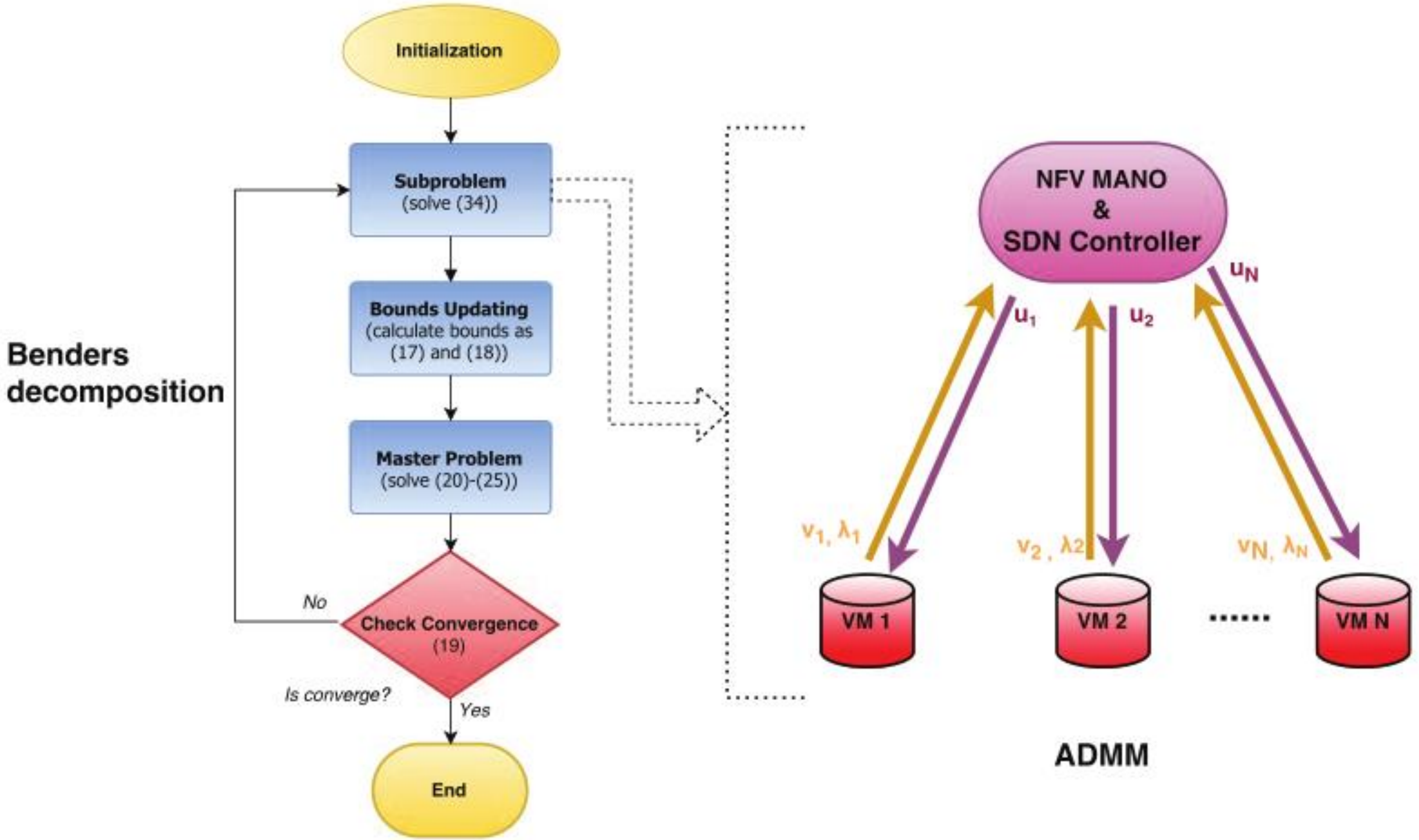
Proposed Algorithm



Benders Decomposition

- General MILP

$$\underset{x_1,\ldots,x_n;\, y_1,\ldots,y_m}{\text{minimize}} \quad \sum_{i=1}^{n} c_i\, x_i + \sum_{j=1}^{m} d_j\, y_j$$

subject to

$$\sum_{i=1}^{n} a_{\ell i}\, x_i + \sum_{j=1}^{m} e_{\ell j}\, y_j = b_\ell; \quad \ell = 1,\ldots,q$$

$$x_i^{\text{down}} \le x_i \le x_i^{\text{up}}, \qquad x_i \in \mathbb{N}; \qquad i = 1,\ldots,n$$

$$y_j^{\text{down}} \le y_j \le y_j^{\text{up}}, \quad y_j \in \mathbb{R}; \qquad j = 1,\ldots,m\,.$$

Benders Decomposition

Step 0: Initialization. Initialize the iteration counter, $\nu = 1$, and let

$$x_i^{(\nu)} = \begin{cases} x_i^{\text{down}} & \text{if } c_i \geq 0 \\ x_i^{\text{up}} & \text{if } c_i < 0 \end{cases}$$

$$\alpha^{(\nu)} = \alpha^{\text{down}}$$

Step 1: Subproblem solution. Solve the LP subproblem

$$\underset{y_1,\ldots,y_m}{\text{minimize}} \quad \sum_{j=1}^{m} d_j \, y_j$$

subject to

$$\sum_{j=1}^{m} e_{\ell j} \, y_j = b_\ell - \sum_{i=1}^{n} a_{\ell i} \, x_i; \quad \ell = 1, \ldots, q$$

$$y_j^{\text{down}} \leq y_j \leq y_j^{\text{up}}, \qquad y_j \in \mathbb{R}; \quad j = 1, \ldots, m$$

$$x_i = x_i^{(\nu)} : \quad \lambda_i; \quad i = 1, \ldots, n \, .$$

The solution of this problem is $y_1^{(\nu)}, \ldots, y_m^{(\nu)}$ with dual variable values $\lambda_1^{(\nu)}, \ldots, \lambda_n^{(\nu)}$.

Benders Decomposition

Step 2: Convergence checking. Compute upper and lower bounds of the optimal value of the objective function of the original problem

$$z_{\text{up}}^{(\nu)} = \sum_{i=1}^{n} c_i \, x_i^{(\nu)} + \sum_{j=1}^{m} d_j \, y_j^{(\nu)}$$

$$z_{\text{down}}^{(\nu)} = \sum_{i=1}^{n} c_i \, x_i^{(\nu)} + \alpha^{(\nu)} \, .$$

If $z_{\text{up}}^{(\nu)} - z_{\text{down}}^{(\nu)}$ is smaller than a pre-specified tolerance, stop, the optimal solution is $x_1^{(\nu)}, \ldots, x_n^{(\nu)}$ and $y_1^{(\nu)}, \ldots, y_m^{(\nu)}$. Otherwise, the algorithm continues with the next step.

Benders Decomposition

Step 3: Master problem solution. Update the iteration counter, $\nu \leftarrow \nu+1$. Solve the MILP master problem

$$\underset{x_1,\ldots,x_n,\alpha}{\text{minimize}} \quad \sum_{i=1}^{n} c_i x_i + \alpha$$

subject to

Benders cut

$$\alpha \geq \sum_{j=1}^{m} d_j y_j^{(k)} + \sum_{i=1}^{n} \lambda_i^{(k)}(x_i - x_i^{(k)}); \quad k = 1,\ldots,\nu-1$$

$$x_i^{\text{down}} \leq x_i \leq x_i^{\text{up}}, \qquad x_i \in \mathbb{N}; \quad i = 1,\ldots,n$$

$$\alpha \geq \alpha^{\text{down}} \ .$$

The solution of this problem is $x_1^{(\nu)},\ldots,x_n^{(\nu)}$ and $\alpha^{(\nu)}$. The algorithm continues with Step 1. $\square$

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Alternating Direction Method of Multipliers (ADMM) to solve subproblems

$$\boxed{\begin{array}{ll} \min & f(x) + g(z) \\ \text{s.t.} & Ax + Bz = c. \end{array}}$$

Augmented Lagrangian function

$$\mathcal{L}(x, z, \lambda) = f(x) + g(z) + \lambda^T(Ax + Bz - c) + \frac{\rho}{2}||Ax + Bz - c||^2$$

Iterative procedure to solve an optimization problem using ADMM

$$x[t+1] := \arg\min_x \mathcal{L}(x, z[t], \lambda[t]),$$

California government

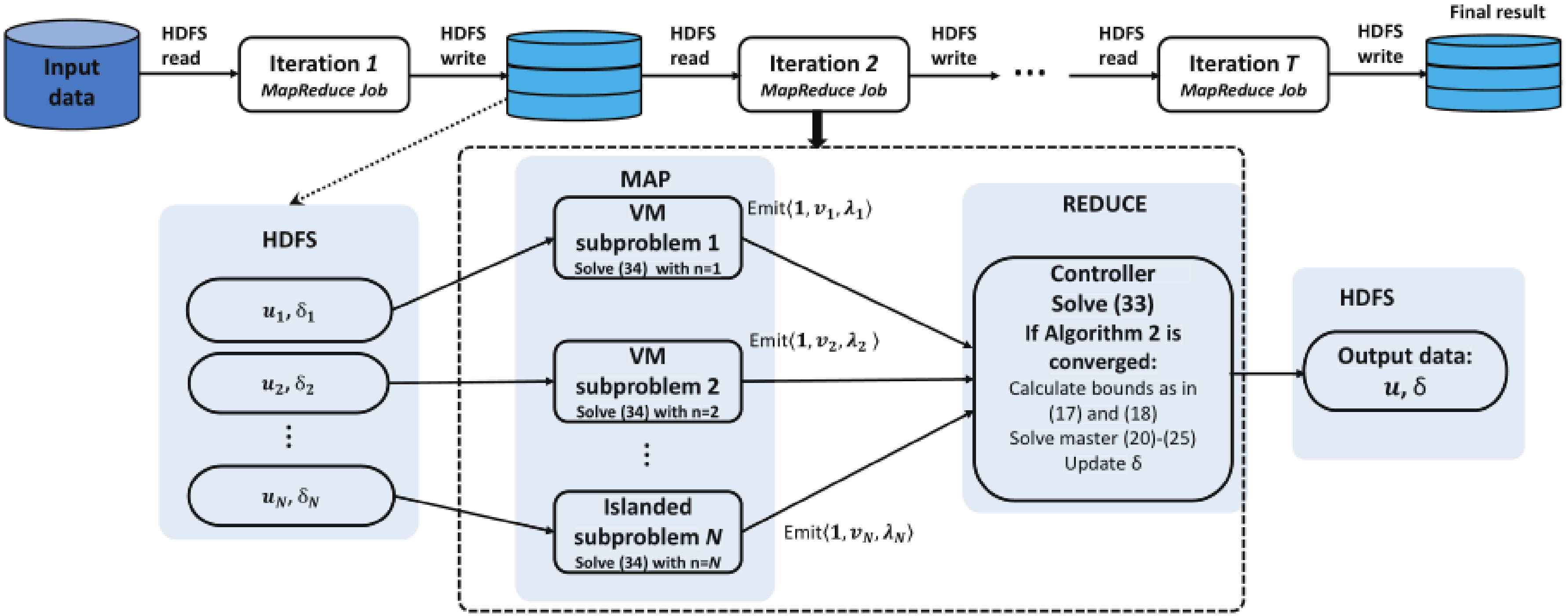
$$z[t+1] := \arg\min_z \mathcal{L}(x[t+1], z, \lambda[t]),$$

Texas government

$$\lambda[t+1] := \lambda[t] + \rho\left(Ax[t+1] + Bz[t+1] - c\right),$$

US Congrress

Implementation using Hadoop MapReduce



Simulation Results

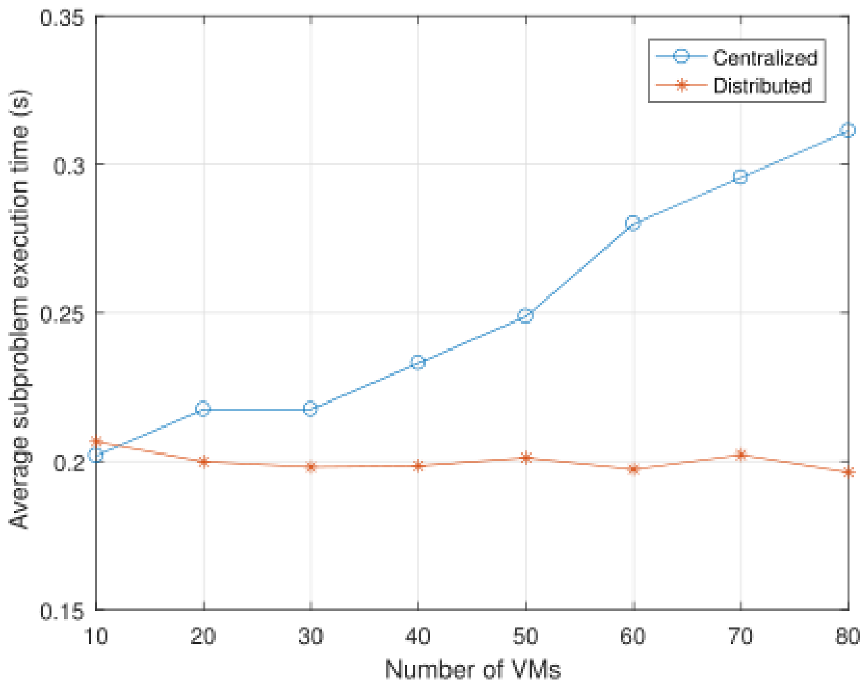


Fig. 9: The average execution time of subproblem versus number of VMs

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  - ❑ **Deep Learning Analysis**
- ❑ **Conclusions**

D2D Communication

- Device-to-Device (D2D) Communications/Sidelink
  - Technology that enables devices to connect directly without relying on infrastructure of access points or base stations.

① Increase network capacity
② Extend (edge) coverage
③ Offload data
④ Improve energy efficiency
⑤ Create new applications

licensed (Inband) spectrum
  - Underlay vs. Overlay
  - UpLink vs. DownLink
  - Mode Selection (D2D mode vs. Cellular Mode)

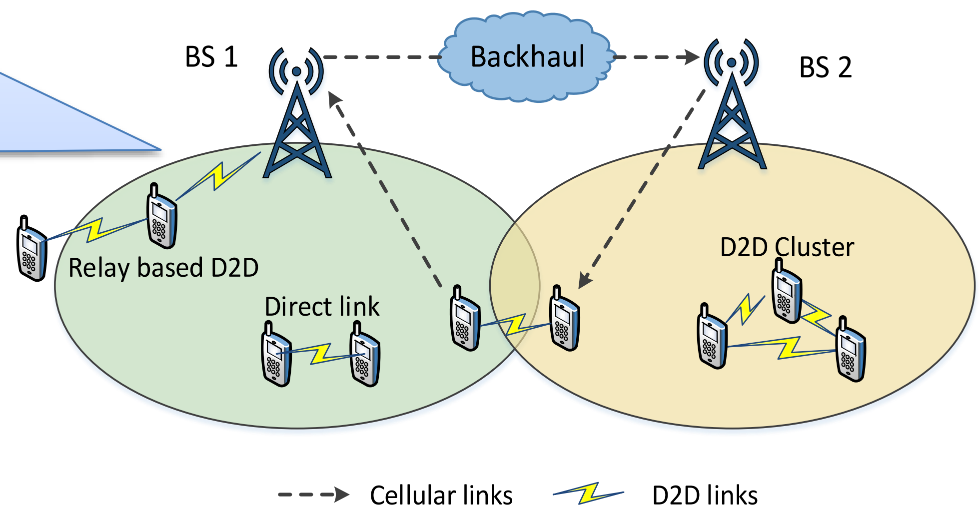


Figure: Scenario of D2D Communications

TS36.300 v12 (2015.02)

section 23.10 for D2D Communications

section 23.11 for D2D Discovery (proximity detection for commercial services)

TS36.211 v12 (2015.10)

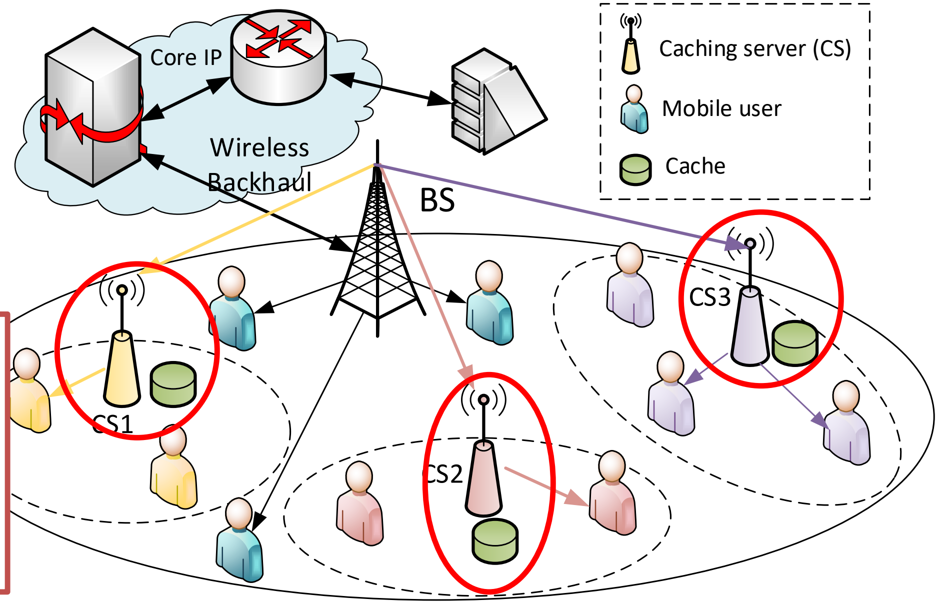
section 9: a sidelink is used for ProSe direct communication and ProSe direct discovery between UEs. (ProSe – Proximity Services)

Exploiting D2D in Mobile Social Network

- Imminent wireless capacity crunch
  - Smartphones with larger storage and higher computing capability
  - Mobile social platforms, e.g.,
  - Virtual and Social Community
    - Social tie (family members, club members…)
    - Social relationship with common interest
    - Social interactions
  - Continuous (uninterrupted) wireless connection
  - File sharing & Online gaming & Video dissemination
- D2D---exploit benefits from social networking
  - in terms of pairs and clusters
  - to offload the increasing traffic from base stations (BSs)
  - to meet the higher speed demands for mobile users

Wireless Distributed Storage Systems

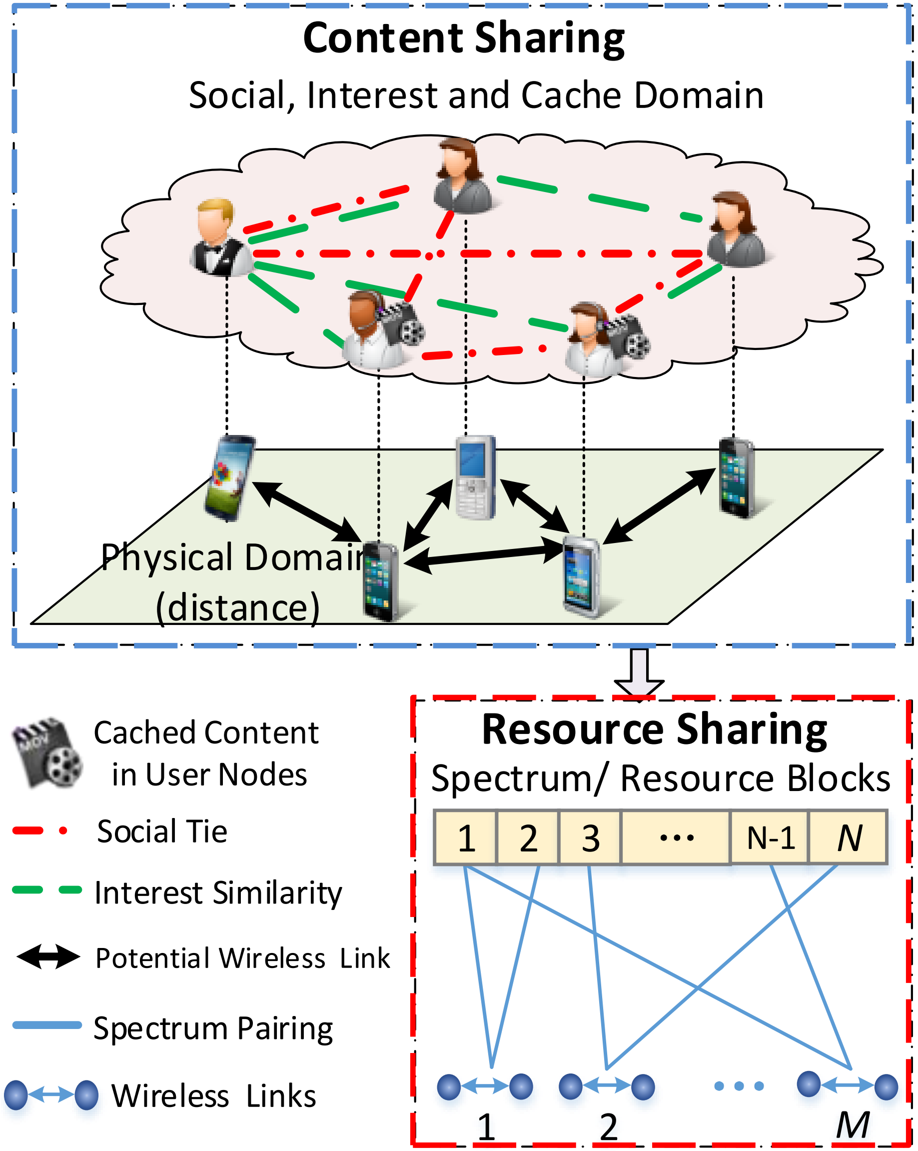
- **Wireless distributed storage:**
  - Store the popular content files at the BS/mobile devices during off-hours to improve the end-to-end performance and reduce backhaul loading at peak-hours
  - Small BS or powerful user nodes
  - Popular files can be received from the BS and stored in their own caching
  - Files in its cache can be accessed by other users within its coverage at a later time
- **Benefits of wireless storage:**
  - Capacity enhancement
  - Backhaul traffic offloading
  - Interference mitigation



- **Wireless caching schemes:**
  - **Coded caching** to create coded multicast opportunities
  - **Proactive caching** to exploit both the spatial and social structure of the wireless networks
  - **D2D caching networks** to reduce number of hops and balance load
  - **Asymptotic scaling laws** in large wireless networks

Focus:
In D2D-based wireless distributed storage systems, resource allocation and content sharing are investigated in different scenarios with different objective functions

D2D-Based Distributed Storage Systems



Upper layer: Content sharing for D2D partners to form Links

Main considerations:

- Social relationship
- Interest similarity
- Physical proximity
- Caching capability
- Computing capability
- Content coding

Lower layer: Resource sharing for CUE and D2D Links in D2D Underlay

Main considerations:

- Channel state information
- Power control
- Co-channel interference

Matching Game Definitions

Basic elements (Stable Marriage (SM)):

1. Agents: A set of men, and a set of women;

2. Preference list: A sorted list of men/women based on her/his preferences;

3. Blocking pair (BP) (m,w):

m prefers w to his current partner;

w prefers m to her current partner;

4. Stable matching: A matching admit no BPs.

5. Gale-Shapley (GS) algorithm: find a stable matching in SM

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GS Algorithm


Adam

Geeta, Heiki, Irina, Fran


Fran


Bob

Irina, Fran, Heiki, Geeta


Geeta

Carl > Adam

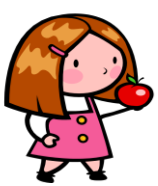

Carl

Geeta, Fran, Heiki, Irina


Heiki


David

Irina, Heiki, Geeta, Fran


Irina

David > Bob

We reach a stable marriage!

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Reinforcement Learning

Effective and Efficient Method

Dummy

Policy
(Machine)

Expert

An Example

Today

1

1

Have Fun

-100

Fencing Event

0

0

1

Study & Discussion

0

IEEE Globecom

Submit Paper

100

Rewards

a: action

s: state

$$
R(s,a) = \begin{array}{c|c}
 & \begin{array}{ccccc} \text{Today} & \text{Study} & \text{Submit} & \text{Fun} & \text{Fencing} \end{array} \\
\begin{array}{c} \text{Today} \\ \text{Study} \\ \text{Submit} \\ \text{Fun} \\ \text{Fencing} \end{array} &
\begin{bmatrix}
-1 & 0 & -1 & 1 & -1 \\
-1 & -1 & 0 & 1 & -1 \\
-1 & -1 & -1 & -1 & 100 \\
-1 & 1 & -1 & 1 & -100 \\
-1 & -1 & -1 & -1 & -1
\end{bmatrix}
\end{array}
$$

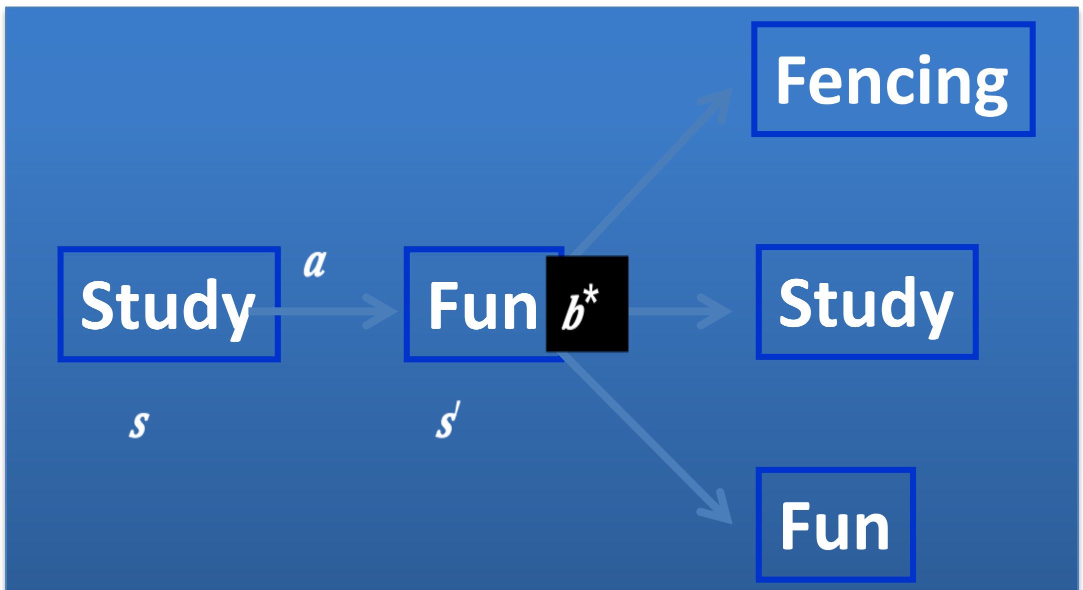
Initially set to zero

Q-Learning

Learning Rate

Discount Factor

$$Q_{t+1}(s,a) = (1-\alpha_t)Q_t(s,a) + \alpha_t\left[R_t(s,a) + \beta \max_b Q_t(s',b)\right]$$

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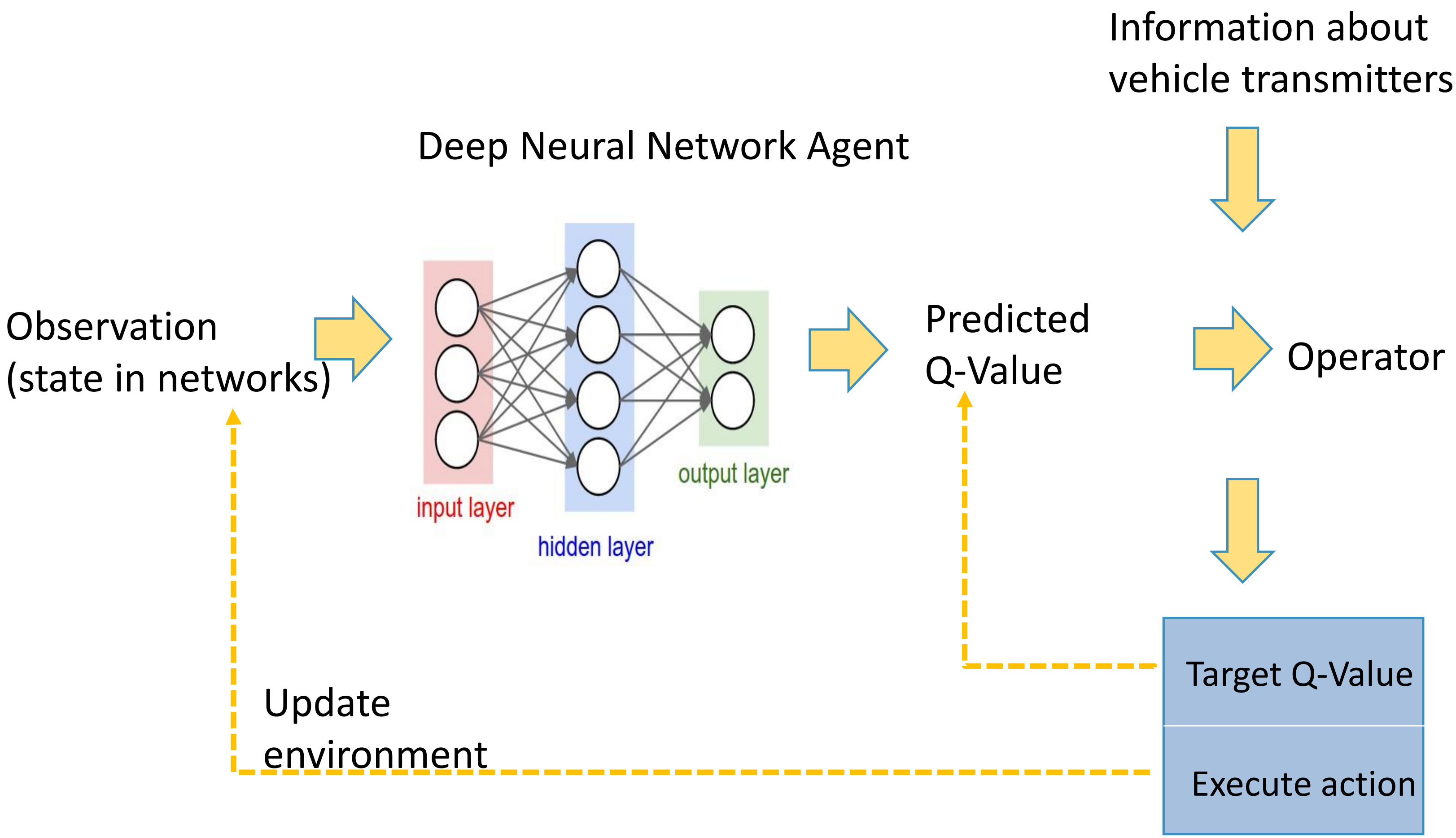
Deep Reinforcement Learning Framework



AlphaGo Zero beats AlphaGo beats Human

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Conclusions

- Communication, Caching and Computing are potential solutions to achieve 5G
- Challenge is how to write utility to link them
- Scenarios vs. solutions
  - Network virtualization based on Benders decomposition and ADMM
  - Mobile social networks over D2D based on matching
  - Deep reinforcement learning
- Just a small peek on a new paradigm

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Thank You!

Proposed Algorithm

$$
\begin{aligned}
\min_{\boldsymbol{\delta}^m \alpha} \quad & Q_p + \alpha \\
\text{s.t} \quad & 1 \leq \sum_{n=1}^{N} \delta_{n,k}^m \leq N \quad \forall k, m, \\
& Q_t(\mathbf{v}^{m,(j)}) + \boldsymbol{\theta}^{m,(j)}(\boldsymbol{\delta}^m - \boldsymbol{\delta}^{m,(j)}) \leq \alpha \quad j = 1, \ldots, l-1, \\
& \sum_{k=1}^{K} \delta_{n,k}^m v_{n,k}^m \phi_k \leq C_n \quad \forall n, m, \\
& \alpha \geq \alpha^{down} \\
& \delta_{n,k}^m \in \{0, 1\} \quad \forall m, n, k,
\end{aligned}
$$

Algorithm 1 NFV Resource al

Initialize: loop index l, $U_{\delta^m_n}$

while $Q_{up}^l - Q_{down}^l \geq \varepsilon$ **do**

Subproblem

acquire $\mathbf{v}^{m(l)}$ and $\boldsymbol{\theta}^m$

Bounds calculation

calculate upper and l

Master problem

step 1: update loop index $l = l + 1$

step 2: add new Benders cut to the problem (20)

step 3: solve the problem (20) to obtain the optimal value of $\boldsymbol{\delta}^m$ and α

end while

Proposed Algorithm

- Transformation of subproblem

$$
\begin{aligned}
\min_{\mathbf{v}^m} \quad & Q_t \\
\text{s.t} \quad & \sum_{k=1}^{K} \delta_{n,k}^m v_{n,k}^m \phi_k \le C_n \quad \forall n, m, \\
& \sum_{n=1}^{N} v_{n,k}^m \ge R_k \quad \forall k, \\
& \mu_{f_k} \le \frac{\sum_{n=1}^{N} v_{n,k+1}^m}{\sum_{n=1}^{N} v_{n,k}^m} \quad \forall k, \\
& \delta_{n,k}^m = \delta_{n,k}^{m,(l)} : \theta_{n,k}^{m,(l)} \quad \forall m, n, k.
\end{aligned}
$$

$\Rightarrow$

$$
\begin{aligned}
\min_{\mathbf{v}^m} \quad & Q_t \\
\text{s.t} \quad & \sum_{k=1}^{K} \delta_{n,k}^m v_{n,k}^m \phi_k \le C_n \quad \forall n, m, \\
& \sum_{n=1}^{N} u_{n,k}^m \ge R_k \quad \forall k, \\
& \mu_{f_k} \sum_{n=1}^{N} u_{n,k}^m - \sum_{n=1}^{N} u_{n,k+1}^m \le 0 \quad \forall k \\
& \delta_{n,k}^m = \delta_{n,k}^{m,(l)} : \theta_{n,k}^{m,(l)} \quad \forall m, n, k \\
& v_{n,k}^m = u_{n,k}^m \quad \forall n, k.
\end{aligned}
$$

Global copy variable

Proposed Algorithm

Algorithm 2 Distributed algorithm for the subproblem based on ADMM

Initialize: t, $\boldsymbol{\lambda}$, $\mathbf{v}$
while the stopping criterion is not satisfied **do**
  Controller update
  repeat
    wait
  until receive updated $\boldsymbol{\lambda}$, $\mathbf{v}$ from all N distributed VMs
   step 1: Solve the problem (44) and obtain the optimal solution $\tilde{\mathbf{u}}$
   step 2: Then send $\tilde{\mathbf{u}}$ to the VMs
   step 3: Update
———
  Each VM u
  repeat
    wait
  until receive
   step 1: So
   step 2: Up
     $\boldsymbol{\lambda}[$
   step 3: Se
end while

$$\min_{\mathbf{v}^{m,(l)}} \quad \sum_{k=1}^{K} \gamma_k v_{n,k}^m + \sum_{k=1}^{K} \lambda_{n,k} + \frac{\rho}{2} \sum_{k=1}^{K} \| v_{n,k}^m - \tilde{u}_{n,k}^m \|_2^2 \tag{45}$$

$$\text{s.t} \quad \sum_{k=1}^{K} \delta_{n,k}^m v_{n,k}^m \phi_k \le C_n \quad \forall m.$$

$$\min_{\mathbf{u}^{m,}}$$

$$\text{s.t} \quad \sum_{n=1} u_{n,k}^m \ge R_k \quad \forall k,$$

$$\mu_{f_k} \sum_{n=1}^{N} u_{n,k}^m - \sum_{n=1}^{N} u_{n,k+1}^m \le 0 \quad \forall k,$$

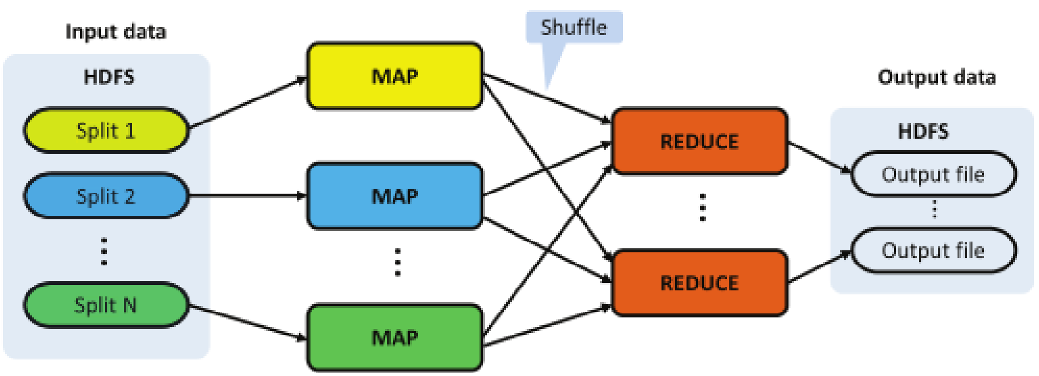
Implementation using Hadoop MapReduce

Algorithm 3 ADMM-based Bender decomposition using Hadoop MapReduce

function MAP(vm_ID, inputData)
  Load data of previous iteration from HDFS corresponding to vm_ID
  Solve subproblem corresponding to each VM in (45)
  Update $\boldsymbol{\lambda}_n$ using (46)
  EMIT $\langle 1, \{\boldsymbol{v}_n, \boldsymbol{\lambda}_n\}\rangle$
end function

function REDUCE(key, Data from Mappers)
  Concatenate $\{\boldsymbol{v}_n, \boldsymbol{\lambda}_n\}$ from all VMs
  Solve controller subproblem (44) for $\boldsymbol{u}$
  if Algorithm 2 is converged **then**
    Calculate Upper bound and Lower bound as in (17) and (18)
    Sove master problem in (20)
    Update $\boldsymbol{\delta}$
  end if
  EMIT $\langle\{\boldsymbol{u}, \boldsymbol{\delta}\}\rangle$
end function

function MAIN(inputPath, outputPath)
  Initialization
  while $Q^l_{up} - Q^l_{down} \geq \varepsilon$ **do**
    run MapReduceJob (inputPath, outputPath)
    $t \leftarrow t + 1$
  end while
end function



Simulation Results

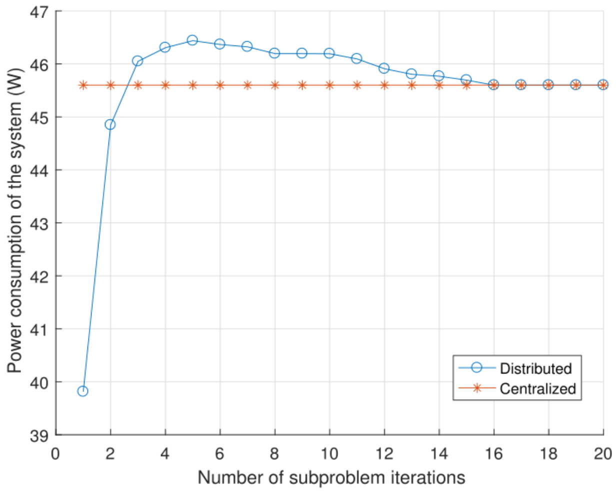


Fig. 6: The convergence performance of ADMM

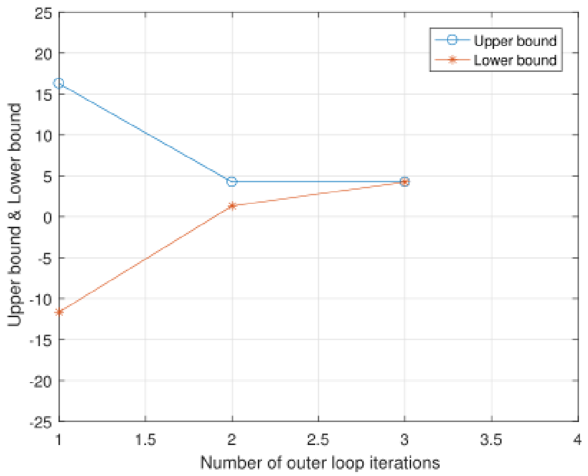


Fig. 7: The convergence performance of Benders decomposition