

## Index

- 5G mobile technology, 1, 2, 277, 303, 308, 385, 406, 436
- ADMM (alternating direction method of multipliers) schemes, 291*fig*, 291–293, 293*fig*, 294, 311, 487
- Aharoni, Ziv, 317
- Amiri, Mohammad Mohammadi, 434
- Auer, P., 254
- autoencoders
  - applications of, 12
  - architecture of, 11*fig*
  - channel coding and, 29, 87*fig*, 87–90, 90*fig*
  - channel feedback and, 131
  - data compression and, 12
  - denoising autoencoders, 12
  - design challenges for, 13
  - history of, 12
  - JSCC and, 28–31
  - NNC and, 57–58
  - overview of, 11–13
  - timely wireless edge inference and, 516
  - variational autoencoders, 6
- autonomous driving, 1, 55, 434, 486, 513
- BCJR (Bahl-Cocke-Jelinek-Raviv) algorithm, 79, 83*fig*, 86*fig*, 81–86, 163–167, 175*fig*, 175, 179
- BCJRNet, 163–167, 175*fig*, 175, 179
- Bengio, Y., 249
- Bennis, Mehdi, 457
- capacity estimation
  - causal conditions for, 320–321
  - channel capacity and, 319–322
  - DDPG algorithm and, 327*fig*, 326–329
  - definition of, 317
  - design challenges for, 322–337
  - DINE and, 340*fig*, 342*fig*, 337–343
  - directed information and, 320–322
  - discrete memoryless channels and, 319
  - estimation without channel models and, 346*fig*, 343–346
  - feedback capacity and, 325–326
- Ising channel case study of, 332*fig*, 332*t*, 334*t*, 332–337, 337*fig*, 337
- learning settings for, 324–325
- mutual information and, 321
- overview of, 15–16, 317–319, 322–337
- policy optimization by unfolding and, 327*fig*, 327–331, 331*fig*
- RL and, 322–337
- unifilar finite-state channels and, 323*t*, 323
- channel coding. *See also* joint source-channel coding
  - adaptive decoding and, 91*fig*, 91–92
  - algorithm deficiency and, 78
  - autoencoders and, 29, 87*fig*, 87–90, 90*fig*
  - BCJR algorithm learning and, 79, 83*fig*, 86*fig*, 81–86
  - convolutional codes and recurrent neural networks and, 80*fig*, 79–81
  - data-driven approaches to, 26*fig*, 28*fig*
  - decoding linear block codes and, 103–104
  - differentially private wireless FL and, 495
  - Hamming codes and, 102*fig*, 102–103, 103*fig*
  - linear blockcodes and, 100–105
  - MAP decoder and, 100*fig*, 100–101, 101*fig*
  - model deficiency and, 78
  - NNC and, 60–61
  - noise and, 99*fig*, 99
  - open problems for, 105–107
  - output feedback and, 94*fig*, 95*fig*, 94–100, 100*fig*
  - overview of, 3, 23–29, 31, 78*fig*, 77–79, 105–107
  - Polar codes and, 100*fig*, 100–101, 101*fig*, 105
  - recovering codes and, 79–90, 100–103
  - results on, 90–100, 103–105
  - robust decoding and, 91*fig*, 91–92, 92*fig*
  - sequential codes and, 79–100
  - signal detection and, 136–137
  - symbol detectors for finite-memory channels and, 92*fig*, 94*fig*, 92–95, 95*fig*, 100*fig*
  - timely wireless edge inference and, 516–517
  - turbo codes and, 81*fig*, 82*fig*, 81–82, 87*fig*, 87–90, 90*fig*
- channel equalization, 3, 29, 233–234

- channel estimation
  - CNN-based channel estimation, 120*fig*, 120–121, 121*fig*
  - definition of, 5
  - further improvement for, 121
  - image communications and, 119–120
  - joint channel estimation, 136, 136*fig*
  - MmWave/Terahertz channel estimation, 112*fig*, 112–114, 114*fig*
  - OFDM channel estimation, 117*fig*, 119*fig*, 117–121
  - overview of, 3, 14, 111
  - signal detection and, 136*fig*, 136, 136*fig*, 138–140
  - wideband terahertz channel estimation, 116*fig*, 114–117
- channel feedback
  - autoencoders and, 131
  - bit-level channel feedback, 129*fig*, 131*t*, 129–133
  - channel reciprocity-based feedback, 129
  - massive MIMO-OFDM CSI feedback, 124*t*, 122–125
  - other feedback methods, 125–127
  - overview of, 122
  - time-varying channel feedback, 125*fig*, 126*t*, 125–127, 127*fig*, 127*t*
- ChannelNet, 120–121
- Chen, Mingzhe, 409
- collaborative learning
  - centralized learning and, 356–357
  - communication efficient distributed ML and, 358–369
  - decentralized learning and, 357–358
  - device selection and, 369–380
  - distributed learning and, 369–380
  - FL and, 367–369
  - hierarchical edge learning and, 377*fig*, 377*t*, 380*fig*, 380*t*, 377–380
- IoT and, 353
  - overview of, 16, 353–356, 380
  - quantization for, 363–366
  - resource allocation and, 369–380
  - sparsification and, 358–363
  - test accuracy of, 370*fig*, 377*fig*
- ComNet, 139–141
- constrained unsupervised learning
  - cases studies for, 199–209
  - centralized approach to, 187–193, 198*fig*, 198–199, 199*fig*
  - cognitive multiple access channels and, 199*fig*, 199–204, 204*fig*
  - cooperative mechanisms and, 185–187
  - distributed approach to, 184–187, 193–199
  - distributed deployment of, 198*fig*, 198–199, 199*fig*
  - interference channels and, 205–209
- learning to optimize and, 188–190
- management of wireless networks and, 184–187
- overview of, 15, 182–184, 209
- stochastic message binarization in, 195–198
- system model for, 182*fig*, 184–185
- Courville, A., 249
- Cui, Shuguang, 285, 409
- data compression, 6, 12, 313
- data-driven wireless networks
  - ADMM and, 291*fig*, 291–293, 293*fig*
  - applications of, 303, 308
  - architecture of, 288*fig*, 289*fig*, 288–289
  - Bayesian non-parametric learning and, 296*fig*, 295–303
  - cloud-based intelligence and, 288–289
  - design challenges for, 313
  - examples for, 296–298
  - fully distributed learning frameworks and, 294
  - future directions for, 313
  - good interpretability of kernal functions and, 296–298
  - IoT and, 286
  - learning models for, 289–308
  - motion modelling and, 311*t*, 309–312
  - motivation for, 285–287
  - on-device intelligence and, 289
  - overview of, 285–287
  - parallel learning frameworks and, 290*fig*, 290–294, 294*fig*
  - practical use cases of, 308–313
  - PSGD and, 293–294
  - RL and, 303–308, 312*fig*, 312*t*
  - scalability and, 288*fig*, 289*fig*, 288–289, 299–301, 306*fig*, 306, 306*fig*
  - traffic prediction and, 308*t*, 309*fig*, 309*t*, 308–310, 310*fig*, 310*t*, 312*fig*, 312*t*
  - uncertainty and, 302–303, 306–307
- DDPG (deep deterministic policy gradient) algorithm, 327*fig*, 326–329
- Debbah, Mérouane, 212
- decoding. *See* channel coding
- DeepCode, 94–100, 105–107
- DeepJSCC. *See* joint source-channel coding
- Deep Learning (DL). *See specific applications of DL*
- Deep Learning (DL) Aided JSCC for images
  - baseline in, 42
  - channel output feedback in, 48
  - channel versatility and, 45*fig*, 44–46
  - decoder in, 40*fig*
  - domain specific communication and, 46–47
  - encoder in, 40*fig*
  - evaluation metrics for, 40–41
  - experimental setup for, 41

- graceful degradation and, 42–44
- hardware implementation for, 49
- overview of, 39
- results of, 44*fig*, 45*fig*, 46*fig*, 49*fig*, 42–49
- successive refinement in, 47
- system model for, 39–41
- visual comparison for, 42
- Deep Learning (DL) Aided JSCL for text**
  - architecture of, 32
  - baselines for, 36–37
  - channel in, 34–35
  - decoder in, 35
  - encoder in, 33–34
  - experimental setup for, 35–37
  - model training details for, 36
  - overview of, 31–32
  - results for, 37*fig*, 37–38, 38*fig*
  - system model for, 32–35
  - variable length encoding in, 34
- Deep Neural Networks (DNNs)**
  - activation functions in, 10
  - architecture of, 8*fig*, 10
  - backpropagation algorithms in, 11
  - deep generative models and, 6
  - deep symbol detection and, 170*fig*, 159–178
  - error functions in, 11
  - feedforward neural networks, 8
  - forward propagation in, 10*fig*
  - impact of, 4
  - JSCL and, 23–24, 30
  - model-based ML and, 146*fig*, 148*fig*, 146–148, 151*fig*, 151, 178–179
  - overview of, 8–11
  - recurrent neural networks, 8
  - signal detection and, 137, 139–141
- DeepSIC**, 170*fig*, 171*fig*, 167–171, 179
- deep symbol detection**
  - BCJRNet** for finite-memory channels and, 163–167, 175*fig*, 175, 179
  - DeepSIC** for Flat MIMO channels and, 170*fig*, 171*fig*, 167–171, 179
  - deep unfolding and, 156–159
  - design process for, 153, 156, 159–160
  - DetNet** for Flat MIMO channels and, 156–159
  - DNN-aided algorithms and, 170*fig*, 159–178
  - established deep networks and, 153–155
  - finite-memory channel evaluation for, 172*fig*, 172–175, 175*fig*
  - Memoryless MIMO channels and, 176*fig*, 176–178
  - numerical study of, 172–178
  - overview of, 152
  - results for, 155–156, 158–159, 172–178
  - SBRNN for finite-memory channels and, 153–155
  - symbol detection problem and, 152–153
  - ViterbiNet for finite-memory channels and, 160–163, 166–167, 175*fig*, 175, 179
- detection. *See* deep symbol detection; signal detection
- DetNet**, 134, 156–159
- differentially private wireless federated learning (FL)**
  - analog transmission and, 499–504
  - assumptions on function loss, 492
  - channel coding and, 495
  - communication model for, 491–492
  - convergence analysis of, 497–498, 501–502
  - digital transmission and, 493–499
  - DP mechanism and, 495
  - notation for, 488–493
  - numerical results for, 504*fig*, 504–506, 506*fig*
  - overview of, 16, 486–488, 506–507
  - performance analysis and, 496–498, 500–502
  - power allocation and, 502–504
  - privacy and, 486, 489–490, 496–497, 500–502
  - quantization for, 493–495
  - rate allocation policy and, 498–499
  - system model for, 488*fig*, 488–493
  - transmission scheme description for, 499–500
- DINE (DI neural estimator)**, 318–319, 340*fig*, 342*fig*, 337–343
- DL.** *See* Deep Learning
- edge inference.** *See* timely wireless edge inference
- Effros, M.**, 55
- Eldar, Yonina**, 1, 145, 409
- encoders.** *See* autoencoders; channel coding
- estimation.** *See* capacity estimation; channel estimation
- Farsad, Nariman**, 23, 145
- FedAvg (Federated Averaging) algorithm**, 390*fig*, 390–391, 391*fig*, 413–414
- federated knowledge distillation**
  - applications of, 465*fig*, 465–468, 468*fig*, 469–477
  - background on, 458–464
  - baseline for, 470–472
  - classification and, 465*fig*, 465–468, 468*fig*
  - co-distillation and, 461*fig*, 464*fig*, 461–464
  - discussion of, 473–476, 481–482
  - experience memory and, 477*fig*, 477–478, 478*fig*
  - experiments for, 481–482
  - FRD and, 477
  - future directions for, 468–469
  - MixFLD and, 469–476
  - numerical evaluation for, 473*fig*, 473*t*, 473–476, 476*fig*, 476*t*
  - overview of, 16, 457*fig*, 457–458, 458*fig*, 464–469, 482–483

- federated knowledge distillation (cont.)
  - proposals for, 472–474
  - proxy experience memory and, 479*fig.*, 479–481, 481*fig.*
  - recent progress on, 468–469
  - RL and, 477*fig.*, 477–482
  - system model for, 458*fig.*, 458–464
  - uplink-downlink asymmetric channels and, 469–477
- federated learning (FL), 16, 367–369, 387, 495.
  - See also* differentially private wireless federated learning; optimized federated learning; quantized federated learning, feedback. *See* channel feedback
- Goldfeld, Ziv, 317
- Goldsmith, Andrea, 1, 23, 145
- Goodfellow, I., 249
- Gündüz, Deniz, 1, 23, 353, 434
- Hamming codes, 102*fig.*, 102–103, 103*fig.*
- He, Hengtao, 145
- Huang, Xiufeng, 512
- image communications. *See* Deep Learning (DL)
  - Aided JSCC for images
- Internet of Things (IoT)
  - collaborative learning and, 353
  - data-driven wireless networks and, 286
  - definition of, 1
  - JSCC and, 25
  - NNC and, 55
  - OAC for DL and, 434
  - optimized FL and, 385
  - RL and, 272
- Ising channel case study, 334*t*, 332–337
- Jin, Shin, 145
- joint source-channel coding (JSCC). *See also*
  - channel coding; Deep Learning (DL) Aided JSCC for images; Deep Learning (DL) Aided JSCC for text
  - autoencoders and, 28–31
  - components of, 24*fig.*
  - data-driven approach to, 30*fig.*
  - DNNs and, 23–24, 30
  - error detection and, 23
  - IoT and, 25
  - overview of, 14, 23–24, 29–31, 49
  - separation-based systems and, 24*fig.*, 24–26
  - signal detection and, 136–140
- Kim, Hyeji, 45
- Kim, Seong-Lyun, 457
- Koivunen, Visa, 231
- Kurka, David, 23
- Lee, Hoon, 182
- Lee, Sang Hyun, 182
- Leung, Kin, 385
- Li, Geoffrey Ye, 145
- Liu, Dongzhu, 486
- machine learning (ML) and communications.
  - See also* specific applications of ML
  - impact of, 1–4
  - overview of, 1–4, 13–17
  - taxonomy of learning problems in, 4–8
  - tools used for system design in, 8–13
- MacKay, David J.C., 295
- Mary, Philippe, 231
- MEC (mobile edge computing), 514*fig.*, 513–514
- MixFLD, 469–476
- Mnih, V., 249
- model-based machine learning (ML)
  - benefits of, 145–146
  - conventional DL and, 148
  - deep unfolded networks and, 147, 150*fig.*, 150–151, 151*fig.*
  - design challenges of, 146–148
  - DNNs and, 146*fig.*, 148*fig.*, 146–148, 151*fig.*, 151, 178–179
  - hybrid algorithms and, 147, 148*fig.*, 151*fig.*, 151
  - leading approaches to, 148–151
  - model-based algorithms and, 149–150
  - overview of, 15, 145–148, 178–179
  - types of, 147
- Moy, Christophe, 231
- multi-armed bandit (MAB) problems, 7, 251–257, 376
- Neal, Radford, 295
- neural network coding (NNC)
  - autoencoders and, 57–58
  - baseline in, 61–64
  - benefits of, 57
  - channel coding and, 60–61
  - channel statistics and, 65–67
  - data-driven approaches to, 56
  - definition of, 57
  - experiments for, 69–73
  - fading channel and, 66–67
  - functional reconstruction and, 56, 67*fig.*, 67–69, 69*fig.*, 72*fig.*, 72–73, 73*fig.*
  - interference and, 65*fig.*, 65
  - IoT and, 55
  - minimum transmission power and, 63*fig.*, 63*t*, 64*fig.*, 64*t*
  - multi-resolution reconstruction and, 70*fig.*, 70
  - non-multicasting and, 67*fig.*, 67, 67*fig.*
  - NP-hard problems in, 55–58, 60*fig.*
  - open questions for, 73–74
  - overview of, 14, 55*fig.*, 57*fig.*, 55–58, 60*fig.*, 73–74

- performance evaluation of, 61*fig*, 62*fig*, 64*fig*, 61–65, 65*fig*
- policies in, 60, 69
- same source for distinct tasks and, 71*fig*, 71–72, 72*fig*
- signal reconstruction and, 56
- system model for, 58–59
- tasks of different complexity and, 69*fig*, 69–70
- technical details for, 74
- topologies and, 64*fig*, 64–65, 65*fig*
- transmission quality of, 62*fig*
- Niu, Zhisheng, 512
- NNC, *See* neural network coding
- NP-hard problems, 14, 55–58, 60*fig*, 268
- Oh, Seungeun, 457
- optimized federated learning (FL)
  - adaptive FL and, 387
  - algorithms for, 387–391
  - convergence analysis and, 393–399
  - definitions for, 387–391
  - experiments for, 402*fig*, 403*t*, 402–404
  - FedAvg and, 390*fig*, 390–391, 391*fig*
  - implementation of, 401–402
  - IoT and, 385
  - learning problems in, 389
  - model training at wireless edge and, 386*fig*, 386
  - overview of, 385–387, 405–406
  - per-sample loss functions for, 388*fig*, 388*t*
  - resource-constrained federated learning and, 392–393
  - solutions for, 393*t*, 396*t*, 399*t*, 393–401
  - system model for, 387*fig*
- over-the-air computation (OAC) for DL
  - Blind FEEL and, 445–449
  - design challenges for, 436
  - digital FEEL and, 439–441
  - experiments for, 452*t*, 449–453
  - FEEL and, 435–437, 441–445
  - IoT and, 434
  - overview of, 16, 434–437, 454
  - system model for, 437*fig*, 437–439
- Ozfatura, Emre, 353
- Park, Jihong, 457
- Permuter, Haim, 317
- Polar codes, 100*fig*, 100–101, 101*fig*, 105
- Poor, H. Vincent, 1, 353, 409
- PSGD (parallel stochastic gradient descent) schemes, 293–294
- Q-learning, 245–247, 249–251, 257–260
- quantized federated learning (FL)
  - background for, 411–415
  - FedAvg and, 413–414
  - mechanisms for, 416–424
- numerical study of, 427–430
- overview of, 16, 409–411, 430–431
- performance analysis for, 424–430
- probabilistic scalar quantization and, 416*fig*, 416–417, 417*fig*
- quantization theory and, 412*fig*, 411–412
- scalar quantization and, 417*fig*, 417
- system model for, 411–415
- theoretical performance of, 424–426
- unified formulation and, 419–424
- vector quantization and, 418*fig*, 419*fig*, 418–419
- Quek, Tony, 182
- radio resource allocation
  - ANNs and, 213–217
  - backpropagation algorithms and, 214
  - complexity-aware resource management and, 221–228
  - embedding and, 216–217
  - energy efficiency maximization and, 219–221
  - importance of, 212–213
  - inference phase in, 225
  - numerical analysis for, 220–221, 226*t*, 226–228
  - overview of, 15, 212–213, 228
  - resource management and, 218–221
  - state-of-the-art review for, 217
  - stochastic gradient descent and, 215–216
  - training processes for, 214, 225–226
- Ramamoorthy, A., 55
- Rao, Milind, 23
- Rasmussen, C. E., 308
- reinforcement learning (RL)
  - adaptability and, 234
  - applications of, 6–8, 15, 234, 257–260
  - background for, 236
  - Bellman equations and, 239–241
  - benefits of, 234
  - bibliographic remarks on, 278–280
  - capacity estimation and, 322–337
  - data-driven wireless networks and, 303–308, 312*fig*, 312
  - deep-reinforcement learning, 13, 235, 248–251, 260–264, 308, 312
  - definition of, 233–234
  - exploration in, 7
  - federated knowledge distillation and, 477*fig*, 477–482
  - IoT and, 272
  - MAB problems and, 7, 251–254, 264–269
  - Markov decision process and, 238*fig*, 237–245, 254–257
  - notations for, 235
  - overview of, 6–8, 15, 232–236, 277–278
  - PHY layer and, 257–277

- reinforcement learning (RL) (cont.)  
    policies for, 241–242  
    Q-learning and, 245–247, 257–260  
    real world examples of, 269*fig*, 270*t*, 272*fig*, 273*fig*, 277*t*, 269–277  
    regrets in, 252–253  
    SARSA algorithm and, 245–247  
    upper confidence bound algorithms in, 254  
    value functions and, 239  
ReLU (rectified linear unit), 10  
resource allocation. *See* radio resource allocation  
Rini, Stefano, 486  
RL. *See* reinforcement learning  
  
Saemundsson, S., 308  
SARSA algorithm, 245–247  
Schaul, T., 305  
Seo, Hyowoon, 457  
Shannon, Claude E., 23, 91, 95, 319  
Shannon's separation theorem, 15–16, 23, 25–26, 49  
Shi, Wenqi, 512  
Shlezinger, Nir, 145, 409  
signal detection  
    channel coding and, 136–137  
    channel estimation and, 136*fig*, 136, 138–140  
    DNNs and, 137, 139–141  
    JSCC and, 136–140  
    MIMO detection and, 134*fig*, 133–136  
    OFDM detection, 137–141  
    overview of, 14, 133, 141  
Simeone, Osvaldo, 486  
Sonee, Amir, 486  
source coding, 23–31, 421  
supervised learning, 4–6, 8, 12, 153, 235, 469  
symbol detection. *See* deep symbol detection  
text communications. *See* Deep Learning (DL)  
    Aided JSCC for text  
timely wireless edge inference  
    autoencoders and, 516  
    channel coding and, 516–517  
    device-edge co-inference and, 515–517  
    dynamic compression for, 524*fig*, 524–536  
    experiments for, 521*fig*, 521*t*, 522*fig*, 524*fig*, 521–524, 534*fig*, 534–536, 536*fig*  
    inference-aware scheduling and, 517  
    information augmentation in, 529–532  
    joint source for co-inference and, 516–517  
    MEC and, 514*fig*, 513–514  
    neural network splitting and pruning in, 218–221, 515–516, 518*fig*, 520*fig*  
    overview of, 17, 512–514, 536  
    packet loss-aware evolutionary retransmission and, 533  
    profiling and split point selection in, 520–521  
    system model for, 515*fig*  
Tsur, Dor, 317  
Tuor, Tiffany, 385  
  
unsupervised learning, 6, 233–235, 469  
    *See also* constrained unsupervised learning  
  
Van Hasselt, H., 251–254, 305  
ViterbiNet, 93*fig*, 92–95, 160–163, 166–167, 175*fig*, 175, 179  
  
Wang, Shiqiang, 385  
Wang, Z., 305  
  
Xu, Yue, 285  
  
Ye, Hao, 145  
Yin, Feng, 285  
  
Zappone, Alessio, 212  
Zhou, Sheng, 512