Comprehensive Analysis of Core Components in AI & Robotics: Agents, Planning, Learning, Reasoning, Robotics, and Perception

June 9, 2025

1 Intelligent Agents: Embodying Intelligence in Autonomous Systems

The concept of intelligent agents represents one of the most fundamental paradigms in artificial intelligence, serving as the theoretical and practical foundation for creating systems that can operate autonomously in complex environments. An intelligent agent, as defined in leading AI literature, is an entity that perceives its environment, takes actions autonomously to achieve goals, and may improve its performance through machine learning or by acquiring knowledge [1]. This definition encapsulates the essential characteristics that distinguish intelligent systems from mere computational tools: environmental awareness, autonomous decision-making, goal-directed behavior, and adaptive capabilities.

The theoretical framework of intelligent agents encompasses a broad spectrum of systems, ranging from simple control mechanisms to highly sophisticated AI systems. A basic thermostat exemplifies the simplest form of intelligent agent, as it perceives environmental temperature, compares it against a target goal, and takes corrective actions to maintain the desired state [1]. At the other end of the spectrum, modern AI agents demonstrate complex reasoning, planning, and learning capabilities that enable them to operate in dynamic, uncertain environments with minimal human intervention.

1.1 Agentic AI and Digital Agency

A specialized subset of intelligent agents known as agentic AI represents a significant advancement in the field, expanding traditional agent concepts by proactively pursuing goals, making decisions, and taking actions over extended periods [1]. This form of digital agency demonstrates novel capabilities in autonomous operation, where systems can maintain persistent goals and adapt their strategies based on changing circumstances. Agentic AI systems exemplify the evolution from reactive to proactive intelligence, capable of initiating actions based on anticipated needs rather than merely responding to immediate stimuli.

The emergence of agentic AI has been particularly pronounced following the development of large language models and foundation models like GPT-4, which have enabled researchers to experiment with building autonomous systems through projects like AutoGPT and BabyAGI [2]. These systems demonstrate the potential for AI agents to operate with increasing levels of autonomy, handling complex tasks that require sustained attention and adaptive problem-solving over extended timeframes.

1.2 Agent Architectures and Design Patterns

Contemporary research in AI agent implementations has revealed several key architectural patterns that enable enhanced reasoning, planning, and tool execution capabilities [2]. Single-agent architectures focus on developing comprehensive capabilities within individual systems, while multi-agent architectures leverage distributed intelligence through coordinated interactions between multiple specialized agents. The choice between these architectural approaches depends on the complexity of the target domain and the specific requirements for collaboration and task distribution.

Agent communication styles represent another critical design consideration, with different patterns enabling various forms of coordination and knowledge sharing. Leadership structures within multi-agent systems can significantly impact overall system performance, with centralized coordination often providing more predictable behavior while distributed leadership can offer greater resilience and adaptability [2]. These architectural considerations are fundamental to developing robust AI agent systems that can operate effectively in real-world environments.

2 Planning: Deciding Actions Through Systematic Reasoning

Automated planning and scheduling, often referred to simply as AI planning, constitutes a crucial branch of artificial intelligence that focuses on the realization of strategies or action sequences for execution by intelligent agents, autonomous robots, and unmanned vehicles [3]. Unlike classical control and classification problems, planning solutions are inherently complex and must be discovered and optimized in multidimensional space, requiring sophisticated algorithms that can handle uncertainty, resource constraints, and temporal dependencies.

The fundamental planning problem involves synthesizing a plan that, when applied to any of the initial states, will generate a state containing the desired goals [3]. This process requires a description of possible initial states, a clear specification of desired goals, and a comprehensive understanding of available actions and their effects. The resulting plans must be both feasible and optimal, satisfying various constraints while maximizing performance metrics relevant to the specific application domain.

2.1 Planning Problem Classifications and Complexity

The difficulty of planning problems depends significantly on the simplifying assumptions employed and the characteristics of the environment in which the agent operates.

Several key dimensions define the complexity of planning problems: action determinism versus non-determinism, discrete versus continuous state variables, observability levels, and the number of initial states [3]. Deterministic environments allow for more straightforward planning approaches, as the outcomes of actions are predictable. In contrast, non-deterministic environments require probabilistic reasoning and contingency planning to handle uncertain action outcomes.

State variable representation plays a crucial role in planning complexity, with discrete variables typically enabling more tractable planning algorithms compared to continuous state spaces. Observability represents another critical factor, where full observability allows agents to have complete knowledge of the current state, while partial observability requires sophisticated inference mechanisms to maintain accurate world models [3]. These factors collectively determine the computational complexity and the types of algorithms most suitable for specific planning scenarios.

2.2 Advanced Planning Techniques and Applications

Modern planning systems employ sophisticated optimization techniques including dynamic programming, reinforcement learning, and combinatorial optimization to discover effective action sequences [3]. These approaches enable planning in dynamically unknown environments where strategies must be revised online and models must be adapted based on new information. The integration of machine learning techniques with traditional planning methods has led to more robust and adaptive planning systems capable of improving their performance through experience.

Industrial applications of automated planning tools demonstrate the practical value of these systems across various domains. Work order allocation represents a particularly relevant application where planning tools combine artificial intelligence with designed algorithms to schedule tasks, resources, and activities efficiently [4]. The Automated Planning Tool (APT) methodology employs mixed-integer nonlinear programming (MINLP) solvers to handle the complex and nonlinear nature of resource allocation problems, using branch-and-bound methods to eliminate suboptimal solutions and identify efficient scheduling strategies [4].

3 Learning: Improving Through Experience and Data

Machine learning represents the fundamental mechanism through which AI systems acquire and improve their capabilities over time, enabling computers and machines to imitate human learning processes, perform tasks autonomously, and enhance their performance through experience and exposure to data [5]. This capacity for continuous improvement distinguishes intelligent systems from static computational programs, allowing them to adapt to new situations and optimize their behavior based on accumulated experience.

The learning paradigm in artificial intelligence encompasses multiple approaches, each suited to different types of problems and data availability scenarios. The three primary categories of machine learning—supervised learning, unsupervised learning, and reinforcement learning—provide distinct mechanisms for knowledge acquisition and skill development [5]. Understanding these approaches and their applications is crucial for developing AI systems that can effectively learn and adapt in various operational contexts.

3.1 Supervised Learning and Pattern Recognition

Supervised learning utilizes labeled datasets to train algorithms for data classification and outcome prediction, representing the most widely applied machine learning approach in practical AI systems [5]. This methodology requires extensive labeled training data where input-output relationships are explicitly provided, enabling algorithms to learn patterns and associations that can be generalized to new, unseen data. The cross-validation process ensures that models avoid overfitting or underfitting, maintaining robust performance across diverse datasets.

Common supervised learning methods include neural networks, Naïve Bayes classifiers, linear and logistic regression, random forests, and support vector machines [5]. Each approach offers distinct advantages for specific types of problems, with neural networks excelling in complex pattern recognition tasks, while linear methods provide interpretable results for simpler relationships. The choice of algorithm depends on factors such as data complexity, interpretability requirements, and computational constraints.

3.2 Unsupervised Learning and Discovery

Unsupervised learning algorithms analyze and cluster unlabeled datasets without explicit target outputs, discovering hidden patterns and data groupings through automated analysis [5]. This approach proves particularly valuable for exploratory data analysis, customer segmentation, and dimensionality reduction tasks where the goal is to understand inherent data structures rather than predict specific outcomes. Principal component analysis (PCA) and singular value decomposition (SVD) represent common dimensionality reduction techniques that enable efficient processing of high-dimensional datasets [5].

The ability of unsupervised learning systems to identify similarities and differences in data makes them ideal for applications requiring pattern discovery and structure identification. These systems can reveal previously unknown relationships within datasets, providing insights that inform subsequent supervised learning efforts or support decision-making processes in domains where labeled data is scarce or expensive to obtain.

3.3 Reinforcement Learning and Decision Optimization

Reinforcement learning (RL) represents the science of decision-making, focusing on learning optimal behavior in environments to obtain maximum reward through interactions and observations [6]. Unlike supervised learning, reinforcement learning operates without explicit supervision, requiring agents to independently discover action sequences that maximize cumulative rewards through trial-and-error exploration. This approach closely mimics natural learning processes where behaviors are shaped by their consequences.

The reinforcement learning framework involves an agent exploring an unknown environment to achieve specific goals, based on the hypothesis that all objectives can be described through maximization of expected cumulative reward [6]. The formal mathematical framework borrows from optimal control theory and Markov Decision Processes (MDP), providing a rigorous foundation for algorithm development and analysis. The value function $V(s)$ represents a crucial abstraction that captures the expected cumulative reward from a given state s, enabling agents to evaluate the long-term consequences of their actions:

$$V(s) = E\left[\sum_{t=0}^{\infty} \gamma^t r_{t+1} \middle| S_0 = s\right]$$

where γ represents the discount factor and r_t denotes the reward at time t [6].

3.4 Deep Learning and Neural Network Architectures

Deep learning, as a specialized form of machine learning, utilizes artificial neural networks inspired by human brain structures to process and learn from complex data patterns [7]. These networks consist of multiple layers of interconnected nodes, where each layer learns increasingly abstract features from the input data. In image recognition applications, initial layers might identify edges and simple patterns, while deeper layers recognize complex objects and semantic concepts [7].

The training process in deep learning involves adjusting connection weights between nodes to optimize the network's ability to classify or predict outcomes accurately. This process can employ supervised learning with labeled datasets, unsupervised learning for pattern discovery, or reinforcement learning for sequential decision-making tasks [7]. The scalability of deep learning approaches enables processing of vast amounts of unstructured data, making them particularly effective for applications involving images, text, and speech.

4 Reasoning: Inferring with Logic and Knowledge

Reasoning in artificial intelligence encompasses the computational processes that enable systems to derive new information from existing knowledge, make logical inferences, and solve complex problems through systematic analysis. This capability distinguishes intelligent systems from simple data processing tools, enabling them to understand relationships, draw conclusions, and make decisions based on incomplete or uncertain information. Modern AI agent architectures incorporate sophisticated reasoning mechanisms that enable enhanced problem-solving capabilities across diverse domains [2].

The integration of reasoning capabilities with other AI components creates synergistic effects that enhance overall system performance. Contemporary AI agent implementations demonstrate how reasoning, planning, and tool execution can be combined to achieve complex goals that would be impossible with individual components alone [2]. These systems employ various reasoning strategies including logical deduction, probabilistic inference, and analogical reasoning to navigate complex problem spaces and generate appropriate responses to novel situations.

4.1 Logical Reasoning and Knowledge Representation

Logical reasoning forms the foundation of many AI reasoning systems, providing formal methods for representing knowledge and deriving valid conclusions from premises. Propositional logic and first-order predicate logic offer structured frameworks for encoding domain knowledge and implementing inference procedures. These systems can represent complex relationships between entities and apply logical rules to derive new facts from existing knowledge bases.

The effectiveness of logical reasoning systems depends critically on the quality and completeness of their knowledge representations. Well-designed knowledge bases must capture relevant domain information while maintaining consistency and enabling efficient inference procedures. Advanced reasoning systems often employ non-monotonic logics that can handle exceptions and contradictions, enabling more flexible and realistic modeling of real-world scenarios where information may be incomplete or subject to revision.

4.2 Probabilistic Reasoning and Uncertainty Management

Probabilistic reasoning addresses the challenge of making decisions and drawing conclusions under uncertainty, which is ubiquitous in real-world applications. Bayesian networks and other probabilistic graphical models provide systematic frameworks for representing uncertain knowledge and computing posterior probabilities based on observed evidence. These approaches enable AI systems to quantify confidence levels in their conclusions and make rational decisions even when complete information is unavailable.

The mathematical foundation of probabilistic reasoning relies on Bayes' theorem, which provides a principled method for updating beliefs based on new evidence:

$$P(H|E) = \frac{P(E|H) \cdot P(H)}{P(E)}$$

where $P(H|E)$ represents the posterior probability of hypothesis H given evidence E, $P(E|H)$ is the likelihood of observing evidence E under hypothesis H, and $P(H)$ is the prior probability of hypothesis H [6]. This framework enables systematic belief updating and rational decision-making under uncertainty.

4.3 Reasoning in Multi-Agent Systems

Multi-agent reasoning introduces additional complexity as systems must coordinate their inference processes and share knowledge effectively. Communication protocols and information sharing mechanisms become crucial for maintaining consistency across distributed reasoning processes [2]. Different agent architectures employ various strategies for coordinating reasoning activities, from centralized knowledge bases to distributed consensus mechanisms that enable collective intelligence emergence.

The design of reasoning capabilities in multi-agent systems must balance computational efficiency with coordination overhead. Effective systems often employ hierarchical reasoning structures where different agents specialize in specific domains or reasoning tasks, contributing their expertise to collective problem-solving efforts. This distributed approach can enhance robustness and scalability while enabling specialization that improves overall system performance.

5 Robotics: Acting in the World as Embodied Intelligence

Robotics represents the physical manifestation of artificial intelligence, where computational intelligence is embodied in mechanical systems capable of perceiving, reasoning, and acting in the physical world. The integration of AI technologies with robotic platforms creates systems that can operate autonomously in complex, dynamic environments, performing tasks that require both cognitive capabilities and physical manipulation skills. This convergence of artificial intelligence and robotics has led to significant advances in autonomous vehicles, manufacturing automation, service robots, and exploration systems.

The embodiment of intelligence in robotic systems presents unique challenges that distinguish robotics from purely computational AI applications. Physical constraints, sensor limitations, actuator dynamics, and real-time processing requirements create a complex design space where AI algorithms must be adapted to operate effectively within the constraints of physical systems. Successful robotic systems must seamlessly integrate perception, reasoning, planning, and control to achieve reliable autonomous operation.

5.1 Autonomous Robot Architecture and Control

Modern autonomous robots employ hierarchical control architectures that integrate high-level AI reasoning with low-level control systems. These architectures typically include mission planning layers that determine overall objectives and strategies, tactical planning layers that generate specific action sequences, and reactive control layers that handle immediate responses to environmental changes. This multi-level approach enables robots to operate effectively across different temporal scales, from long-term mission objectives to millisecond-level motor control.

The planning and scheduling capabilities discussed earlier become particularly critical in robotic applications where actions have irreversible physical consequences [3]. Robotic planning systems must consider physical constraints such as actuator limitations, collision avoidance, and energy consumption while generating feasible action sequences. The uncertainty inherent in physical environments requires robust planning algorithms that can adapt to unexpected situations and recover from failures gracefully.

5.2 Sensor Integration and Environmental Interaction

Robotic systems rely on sophisticated sensor suites to perceive and understand their environments, integrating information from multiple modalities including vision, touch, proprioception, and potentially other sensory capabilities. The fusion of multi-modal sensor data creates rich environmental representations that enable robust decision-making and precise manipulation tasks. Advanced sensor processing algorithms extract relevant features from raw sensor data, enabling higher-level reasoning about environmental states and dynamics.

The challenge of real-time sensor processing in robotic systems requires efficient algorithms that can maintain high-frequency operation while providing accurate environmental understanding. Machine learning techniques, particularly deep learning approaches, have revolutionized robotic perception by enabling direct learning from raw sensor data [7]. These systems can automatically discover relevant features and patterns that support effective decision-making without requiring hand-crafted feature engineering.

5.3 Human-Robot Interaction and Collaboration

Modern robotics increasingly emphasizes collaborative systems that work alongside humans in shared environments. These systems must understand human intentions, predict human actions, and coordinate their activities to achieve shared objectives safely and efficiently. Natural language processing, gesture recognition, and social reasoning capabilities enable robots to communicate effectively with human collaborators and adapt their behavior to human preferences and working styles.

Safety considerations become paramount in human-robot collaboration scenarios, requiring robust monitoring systems and fail-safe mechanisms that can prevent harmful interactions. These systems must maintain awareness of human presence and activities while performing their tasks, implementing appropriate safety margins and emergency stop procedures when necessary.

6 Perception: Processing Sensory Information for Environmental Understanding

Perception in artificial intelligence and robotics encompasses the computational processes that transform raw sensory data into meaningful representations of the environment, enabling intelligent systems to understand and interact with their surroundings effectively. This capability forms the foundation for all higher-level cognitive functions, as accurate environmental understanding is prerequisite for effective planning, reasoning, and action execution. Modern perception systems integrate multiple sensory modalities and employ sophisticated algorithms to extract relevant information from complex, noisy sensor data.

The evolution of perception capabilities has been dramatically accelerated by advances in deep learning and computer vision technologies [7]. These approaches enable automatic feature learning from raw sensory data, eliminating the need for hand-crafted feature extractors and enabling more robust and generalizable perception systems. Contemporary perception systems can process visual, auditory, tactile, and other sensory inputs to create rich, multi-modal representations of environmental states and dynamics.

6.1 Computer Vision and Visual Processing

Computer vision represents one of the most advanced areas of AI perception, enabling systems to extract meaningful information from visual imagery through sophisticated image processing and pattern recognition algorithms. Deep learning approaches have revolutionized computer vision by enabling direct learning from pixel-level data to high-level semantic understanding [7]. Convolutional neural networks excel at identifying spatial patterns and hierarchical features in images, enabling robust object recognition, scene understanding, and visual tracking capabilities.

The mathematical foundations of computer vision involve complex transformations between different representational spaces. Camera calibration and geometric transformations enable mapping between 2D image coordinates and 3D world coordinates, supporting accurate spatial understanding and navigation. Optical flow algorithms track visual motion patterns, enabling estimation of object velocities and environmental dynamics that inform planning and control decisions.

6.2 Multi-Modal Sensor Fusion

Advanced perception systems integrate information from multiple sensor modalities to create more robust and complete environmental representations than any single sensor could provide. Vision, lidar, radar, ultrasonic, and other sensors each offer unique advantages and limitations, with sensor fusion algorithms combining their strengths while compensating for individual weaknesses. Kalman filters and particle filters provide mathematical frameworks for combining uncertain sensor measurements while maintaining probabilistic estimates of environmental states.

The temporal dimension of perception requires sophisticated algorithms that can track environmental changes over time and predict future states based on observed dynamics. Sequential estimation techniques enable perception systems to maintain consistent world models despite sensor noise and temporary occlusions, supporting robust decision-making in dynamic environments.

6.3 Perception for Intelligent Agents

The integration of perception capabilities with intelligent agent architectures creates systems that can adapt their behavior based on environmental observations and learned experiences [1]. Perception systems must provide environmental information in formats that support effective reasoning and planning, requiring careful design of representational interfaces between perception and cognition. Modern agent architectures employ perception systems that can learn to extract task-relevant information while filtering out irrelevant details, enabling efficient and focused processing.

The feedback loop between perception and action enables intelligent systems to actively explore their environments and gather information that supports their objectives. Active perception strategies involve deliberate sensor positioning and attention direction to optimize information gathering for specific tasks, representing a form of intelligent sensor management that enhances overall system performance.

7 Conclusion

The comprehensive analysis of these six fundamental components—agents, planning, learning, reasoning, robotics, and perception—reveals the intricate interdependencies that characterize modern AI and robotics systems. Each component contributes essential capabilities while depending on others for complete functionality, creating a synergistic ecosystem where the whole exceeds the sum of its parts. Intelligent agents provide the organizational framework for autonomous operation, while planning systems enable goal-directed behavior through systematic action selection. Learning mechanisms ensure continuous improvement and adaptation, while reasoning capabilities enable intelligent inference and problem-solving under uncertainty.

The physical embodiment of these capabilities in robotic systems demonstrates the practical potential of artificial intelligence to impact the real world through autonomous operation in complex environments. Perception systems provide the essential interface between computational intelligence and environmental reality, enabling informed decision-making based on accurate sensory understanding. The continued advancement of these technologies promises increasingly sophisticated AI systems capable of operating autonomously across diverse domains, from manufacturing and transportation to healthcare and exploration.

Future developments in AI and robotics will likely focus on deeper integration between these components, creating more seamless and efficient intelligent systems. The emergence of foundation models and large language models has already begun to transform how these components interact, enabling more flexible and generalizable AI systems. As these technologies continue to mature, we can expect to see increasingly capable autonomous systems that can operate effectively in complex, dynamic environments while maintaining safety and reliability standards appropriate for real-world deployment.

References

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References

[1] https://en.wikipedia.org/wiki/Intelligent_agent

[2] https://arxiv.org/html/2404.11584v1

[3] https://en.wikipedia.org/wiki/Automated_planning_and_scheduling

[4] https://www.amazon.science/blog/automated-planning-tool-makes-work-order-all

[5] https://www.ibm.com/think/topics/machine-learning

[6] https://www.synopsys.com/glossary/what-is-reinforcement-learning.html

[7] https://cloud.google.com/discover/what-is-deep-learning

[8] https://www.ibm.com/think/topics/ai-reasoning

[9] https://milvus.io/ai-quick-reference/what-are-probabilistic-reasoning-models

[10] https://www.intel.com/content/www/us/en/learn/artificial-intelligence-robotics.html

[11] https://en.wikipedia.org/wiki/Robotics

[12] https://en.wikipedia.org/wiki/Computer_vision

[13] https://www.ibm.com/think/topics/ai-agent-perception

[14] https://en.wikipedia.org/wiki/Stanford_Research_Institute_Problem_Solver

[15] https://www.ibm.com/think/topics/ai-agents

[16] https://arxiv.org/abs/2404.11584

[17] https://www.datacamp.com/blog/what-is-machine-learning

[18] https://cloud.google.com/discover/what-are-ai-agents

[19] https://github.com/resources/articles/ai/what-are-ai-agents

[20] https://smythos.com/developers/agent-development/understanding-intelligent-agents/

[21] https://aws.amazon.com/what-is/ai-agents/

[22] https://en.wikipedia.org/wiki/Machine_learning

[23] https://mitsloan.mit.edu/ideas-made-to-matter/machine-learning-explained

[24] https://developers.google.com/machine-learning/crash-course

[25] https://www.linkedin.com/pulse/harnessing-ai-enhanced-logical-inference-lear

[26] https://www.scaler.com/topics/artificial-intelligence-tutorial/probabilistic-reasoning/

[27] https://rai-inst.com

[28] https://www.nature.com/immersive/robotics-ai/index.html

[29] https://www.nvidia.com/en-us/industries/robotics/

[30] https://www.cs.utexas.edu/~yukez/cs391r_fall2020/slides/lecture_robot_perception.pdf

[31] https://research.google/teams/perception/

[32] https://github.com/tansey/strips

[33] https://www.iso.org/artificial-intelligence/machine-learning

[34] https://en.wikipedia.org/wiki/Supervised_learning

[35] https://www.ibm.com/think/topics/supervised-learning

[36] https://aisera.com/blog/ai-reasoning/

[37] https://www.moveworks.com/us/en/resources/ai-terms-glossary/reasoning

[38] https://www.nvidia.com/en-us/glossary/ai-reasoning/

[39] https://www.bigdatawire.com/2025/02/04/what-are-reasoning-models-and-why-you-should-care/

[40] https://milvus.io/ai-quick-reference/what-is-the-role-of-logical-reasoning-in-ai

[41] https://www.anthropic.com/research/reasoning-models-dont-say-think

[42] https://onlinedegrees.sandiego.edu/application-of-ai-in-robotics/

[43] https://builtin.com/robotics

[44] https://www.mdpi.com/2218-6581/9/4/109

[45] https://www.boston-engineering.com/solutions/technical-innovation/robotics/robotics-capabilities/sensor-and-actuator-integration-in-robotics/

[46] https://bernardmarr.com/what-is-the-difference-between-ai-and-robotics/

[47] https://www.ibm.com/think/topics/computer-vision

[48] https://viso.ai/computer-vision/what-is-computer-vision/

[49] https://opencv.org/blog/what-is-computer-vision/

[50] https://azure.microsoft.com/en-us/resources/cloud-computing-dictionary/what-is-computer-vision

[51] https://robotics.umich.edu/research/focus-areas/perception-manipulation/

[52] https://onlinedegrees.sandiego.edu/introduction-to-computer-vision/

[53] https://web.engr.oregonstate.edu/~afern/classes/cs533/notes/strips-intro.pdf

[54] https://people.cs.pitt.edu/~milos/courses/cs1571-Fall07/Lectures/Class19.pdf

[55] https://www.autoblocks.ai/glossary/stanford-research-institute-problem-solver

[56] https://www.cs.toronto.edu/~sheila/2542/s14/A1/bonetgeffner-heusearch-aij01.pdf

[57] https://en.wikipedia.org/wiki/Planning_Domain_Definition_Language

[58] https://en.wikipedia.org/wiki/Partial-order_planning

[59] https://fai.cs.uni-saarland.de/teaching/winter18-19/planning-material/planning02-planning-formalisms-pre-handout-4up.pdf

[60] https://fai.cs.uni-saarland.de/teaching/winter18-19/planning-material/planning07-heuristic-search-pre-handout-4up.pdf